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Weathering the Energy Crisis: Can Tailored Information to Local Governments and Media Spur Climate Action? *

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Abstract

Can evidence tailored to local public actors, that is policy makers and media, increase residential energy efficiency investments? During the 2022 energy crisis, we randomly assigned local authorities in England and Wales to an outreach treatment. Councillors, council officers, and local media in treated authorities received localized estimates of household exposure to rising energy prices and potential savings from retrofits. Treatment increased retrofit installations by 7 percent, mainly through solar photovoltaics, with no detectable change in energy consumption. Installations were concentrated near councilors' homes, a pattern consistent with local diffusion of the information through policy makers.

Keywords: Energy Efficiency; Energy Prices; Field Experiment; Public Policy

JEL CODES: H1; Q48.

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1 Introduction

Improving the energy efficiency of residential buildings is a key challenges of the green transition. Homes account for a substantial share of energy consumption, and energy-inefficient housing exposes households to both high energy bills and volatile energy prices. Residential retrofits are the result of private household decisions and public climate policy. While the decision to insulate a home or install energy-saving technologies is usually made by households, the information, trust, coordination, and political salience surrounding that decision are shaped by local political institutions and political support. This raises an important question: can informing local public actors like politicians and the media of the consequences of climate inaction change household investment behaviour?

The UK is a relevant setting to study this question in. Its housing stock is particularly old and dependent on fossil-fuel heating compared with other European countries, with a high share of households under the threat of fuel poverty (Department for Business, Energy & Industrial Strategy, 2021; Department for Energy Security and Net Zero, 2026). This was especially salient during the 2022 energy price shock triggered by Russia's invasion of Ukraine. In the first few months after the attack, gas prices skyrocketed (Appendix figure A1). This combination of an old housing stock, a large reliance on fossil fuels, and the spike in energy prices put even more people at risk of not being able to pay their bills and sufficiently heat their homes in the winter. Retrofitting residential houses can reduce exposure to shocks by lowering energy consumption, reducing reliance on fossil-fuel heating, and thus shielding households from future price volatility.

Because retrofit decisions are made by households, most policies, public programs, and scientific studies have focused on household-facing interventions like audits (Gillingham and Tsvetanov, 2018), subsidies (Boomhower and Davis, 2014; Holladay et al., 2019; Houde and Aldy, 2017), nudges (Allcott, 2011; Allcott and Rogers, 2014; Allcott and Kessler, 2019), or information treatments (Papineau and Rivers, 2022). While this bottom-up approach is natural, it leaves political and institutional barriers underexplored. If households face barriers related to information acquisition, coordination, knowledge of local support, or trust, interventions that reach political actors who can legitimise and transmit information locally can be

more effective than those targeted at individuals. Local political actors in the UK are well-suited as a target for such interventions, as they regularly communicate with the population and are locally embedded members of their community. Yet, many councils lack coordination, information, and administrative capacities to do so effectively (Reeves, 2016; Wise et al., 2025).

This paper tests whether disseminating tailored academic findings to local political, administrative, and public actors can influence local energy savings policies. To do so, we ran a field experiment in November 2022, providing information via email to councillors, council workers, and local media outlets in randomly selected local authorities across England and Wales. The recipients in the 165 treated authorities received tailored briefs on the predicted impact of the energy crisis and the potential savings that could arise from retrofitting homes in their constituencies. First, we evaluate the immediate impacts of our information treatment on retrofit installations and energy consumption. Second, we study the political dimensions, like party affiliation, behind the engagement with the brief to understand which actors responded to the information and use councillors' residential locations to examine whether and how the information treatment diffused from politicians to households.

We find that our outreach increased retrofit installations in treated authorities by 7% relative to the mean, corresponding to an increase of approximately one additional installation on average. The increase is mainly driven by installations of solar panels. We do not detect, however, a statistically significant reduction in energy consumption in treated local authorities, which is perhaps unsurprising given the size of the retrofit installation response. Nevertheless, the results show that a low-cost information intervention targeted at local political and administrative actors affected realised investment behaviour, not only engagement with the brief or stated interest.

We then ask who engages with our information treatment and how the treatment may have diffused from politicians to households. Overall, actors in richer authorities are less likely to engage. When looking at councillor level engagement, councillors from the Liberal Democrats and independent councillors are especially likely to engage with the information treatment. Using information on councillors' residential addresses, we find that the increase in retrofitting is highly localised in

the immediate vicinity of councillor homes with no detectable spillovers to neighbouring areas. This is consistent with a highly local diffusion mechanism.

This paper contributes to several strands of the literature. We contribute to research on the energy-efficiency gap, which asks why households underinvest in energy-saving upgrades despite their potential benefits (Allcott and Greenstone, 2012; Gerarden et al., 2017). Existing field experiments typically target households directly through measures such as home energy reports, personalised information, or nudges to obtain energy audits (Allcott, 2011; Allcott and Rogers, 2014; Papineau and Rivers, 2022; Holladay et al., 2019). We find that providing locally tailored evidence to councillors, council officers, and local media can increase household retrofit installations. The increase is concentrated near councillors' homes, a pattern consistent with local diffusion of the information.

We also contribute to research on how policymakers respond to evidence (Hjort et al., 2021; Pereira et al., 2024; Geys and Sørensen, 2018; Nielsen, 2014). We extend this work by tracing the effects of providing evidence to local actors on household investment. Our experiment connects research on local governments' capacity to use granular information (Fetzer et al., 2024a; Feld and Fetzer, 2024) with work on how politicians' local ties shape policy outcomes and responsiveness (Harjunen et al., 2023; Kovarek, 2025). The concentration of additional retrofits near councillors' homes is consistent with local diffusion, though it does not establish how the information reached households.

2 Experimental design

In November 2022, we conducted a randomised control trial (RCT) that carried out tailored outreach to randomly selected local governments and local media. We randomised the treatment across 329 Local Authorities (LADs), resulting in 165 treated and 164 control local authorities.[1] The outreach was in the form of an email that was sent to local councillors, local council workers and local media outlets in treatment local authorities. The email header read "New research: How will the

[1] In this paper, we use the terms council and LAD interchangeably.

energy crisis affect households in *Local Authority XY*?".[2]

First, the body of the email contained results from an analysis of the predicted impact of the energy crisis on households in that local authority, characterising the needs of the local population in terms of energy expenditures. Second, the email suggested ways to save energy and estimated the average savings potential in that local authority in monetary and energy consumption terms, characterising the energy efficiency investments that would lead to the largest savings. Third, the email linked to a 12-page brief with additional in-depth analyses and estimations. Specifically, the brief contained information on average increases in energy bills for the whole local authority, as well as along the empirical distribution of energy consumption, how energy saving measures can help fight climate change, the impact of energy saving installations on EPC ratings and other energy efficiency outcomes.

At the end of the email, we outlined concrete, albeit non-tailored, steps local governments could take to facilitate take-up of energy efficiency investments that can reduce both energy use (thus alleviating the impacts of the energy crisis) and fossil fuel consumption (thus reducing pollution and climate change) in the residential sector. We also included contacts to get in touch with our team, offering to help identifying barriers to take-up of energy efficiency installations, as well as designing and testing programs to overcome those barriers. As an example, appendix sections C.1 and C.2 reproduce the email and respective brief we sent to the local authority of Darlington.[3]

Control LADs received no outreach. We stratified randomisation on the following variables: availability of council contacts, availability of local media contacts,[4] an indicator for local elections being held in 2023, energy savings potential, energy performance certificate (EPC) coverage, an indicator for being located in England as opposed to Wales, and coverage by supra-regional media. First, having contacts for council administrators might make our outreach more powerful by reaching individuals with executive power. Similarly, having contacts for local media and

[2]We preregistered the trial in the AEA RCT Registry (AEARCTR-0010308). Appendix D describes deviations from the pre-analysis plan.

[3]The Financial Times published an infographic with a national-level analysis similar to the one in the brief which can be accessed here. These analyses are based on methods and findings published in Fetzer et al. (2024b).

[4]We compiled a list of local media sources from existing media contacts at the University of Warwick and web searches.

having media that cover a district specifically, vs. multiple, might affect the reach and thus impact of our treatment; we do not have media contacts for 51 LADs. Second, whether there will be a council election in 2023 might affect the ability of current officers to act or whether a party might want to include energy efficiency in their campaigns. Third, we anticipated that our outreach might have more substantial effects in areas with higher savings potential. Fourth, whether the council is below the median coverage of energy performance certificates relative to homes registered for council tax purposes affects the precision of the estimates included in our outreach. Finally, whether the council is in England is significant due to the institutional differences between England and Wales, including variations in fuel prevalence, which could affect the impact of our outreach campaign.

Table A1 reports randomisation balance across several variables of interest for heterogeneity analysis that we did not stratify on. These variables include average household income, population, homeownership rate, and the number of Ukrainian refugees who had arrived by the time of randomisation, given the connection between the war in Ukraine and energy prices. Furthermore, we examine indicators of whether the council is controlled by the Labour Party, the Conservative Party, another party, or if there is no overall control.

The treatment and control groups appear balanced in terms of almost all variables: local authorities in the control group are, on average, larger and host more Ukrainian refugees than those in the treatment group. To account for this, we will control for the general population and the Ukrainian refugee population in our analysis. Our randomisation procedure breaks ties within strata in favour of treatment assignment. Thus, there is one local authority more in the treatment group than in the control group.

3 Data

We use several data sources to obtain 1) covariates for stratification and balancing and 2) outcomes, that is energy-saving measures, energy consumption, and engagement with outreach. For each part of the analysis we use a separate set of variables and different levels of aggregation.

3.1 Stratification and balancing variables

To account for the energy efficiency of residential properties across local authorities, we use data from Energy Performance Certificates (EPC) provided by the UK Ministry of Housing, Communities & Local Government. The EPC data is at the property level and includes the EPC rating, hedonic characteristics such as floor area or the number of rooms, as well as consumption and monetary savings potentials derived from suggestions to improve the energy efficiency of a house. From this data, we compute two variables. First, as not every property has an EPC, we calculate EPC coverage by dividing the number of properties in a local authority that have an EPC by the total number of properties in a local authority as reported in council tax data. Second, we use the combined consumption savings potentials.[5] We discretise these measures into above or below median EPC coverage and above and below median savings potential, and we stratify our randomisation on these indicators.

Furthermore, we stratify on a binary variable indicating whether we have media contacts in a local authority, where these contacts were collected manually by web searches and combined with an existing list of media contacts from the University of Warwick, as well as coverage by supranational media, availability of council contacts,[6] hand-collected information on whether a local election was going to taking place in 2023, and an indicator for being in England as opposed to Wales to capture systematic differences in the two regions.

In addition, we explore heterogeneity and balance with respect to the following characteristics. We use population and home ownership data from the UK 2021 census, average household income from the Office for National Statistics small area income estimates, and the number of Ukrainian refugees an authority hosts from the Home Office. Also, we study heterogeneity in treatment engagement with respect to the political party controlling the local authority council. Council control is divided into Labour party councils, Conservative party councils, other control

[5]This measure is taken from Fetzer et al. (2024b) and is defined as the difference in actual and potential energy consumption combining space heating, hot water generation, and electricity use for lighting. The potential level refers to the energy consumption that would be expected if the energy-efficiency improvements recommended in the EPC were implemented.

[6]We acquired contacts of local officials and local council members from Oscar Research, a commercial data provider.

councils, and no overall control councils as measured in the proprietary Oscar Research data.

3.2 Energy efficiency installations and energy consumption

To study the impact of our treatment outreach on energy efficiency investments, we use data on energy efficiency installations, provided by MCS, a large UK firm that certifies low-carbon installations. The data covers a significant and representative proportion of retrofitting installations in the UK for the period November 2022 – May 2024, and is at the address level (Department for Business, Energy & Industrial Strategy, 2022). In our main analysis, we focus on the subset of properties that ever had an MCS-registered installation, as not all installers might report to MCS. We present results for the full set of properties in the appendix. For every retrofitting installation carried out, the data records a variety of installation characteristics. Among them, and most important for our study, the type of technology, the cost of installing, and the installation type (either domestic or commercial use). Using the address postcode, we aggregate the number of installations over all types at the local authority and quarter-year level. Then, we create two outcome variables: the natural logarithm of the total retrofitting installations, capturing the intensive margin, and a binary indicator equal to one if we record at least one installation in a given LAD and quarter-year observation and zero otherwise, capturing the extensive margin.

Energy consumption We gather information on energy consumption at the postcode level from the Department for Energy Security and Net Zero (DESNZ). The data reports total, mean, and median gas and electricity consumption in kWh for each postcode in the UK from 2013 – 2023. Additionally, the data provides information on the number of electricity meters per postcode area, which we treat as a proxy for the number of households. The data reports information for all postcodes that are not identified as disclosive to comply with privacy laws.[7] We create a "per household" measure of energy consumption by adding up total gas and electric-

[7] A postcode is considered disclosive if it contains fewer than five domestic electricity or gas meters, or if the two highest-consuming meters together account for more than 90% of the postcode's total energy consumption.

ity consumption and dividing by the number of domestic electricity meters in a postcode.

3.3 Engagement with outreach

We employ different measures to examine whether and how local politicians and local media outlets react to information provided by researchers.

Local media engagement As for the media, we manually collect newspaper articles that report about our information treatment with the help of Google Alerts and the University of Warwick communications team. If the media outlet is clearly identifiable as a local newspaper it is assigned to the respective local authority. In cases of trans-regional or national media outlets reporting about the research, we classify them as national and do not use these media engagements in our analysis. From this manually collected list of media mentions, we create a binary indicator at the local authority level that equals one if a media outlet in that local authority reported about the brief and zero otherwise.

Local politicians' engagement We construct two measures of the extensive and intensive margin of engagement: *Brief opened* and *Clicks*. These record, respectively, whether and how many times the policy brief with the extensive additional information on energy saving potential and retrofitting installations we sent to a given councillor or council officer was opened. To track engagement with the outreach materials, we generated a unique link to each brief that contained an individual identifier. Recipients could only see a generalised link and were thus not aware of this identifier. The log files of the website where the briefs were stored track the link, and therefore the unique identifier, via which the website is accessed. We count the clicks for the period 19 December 2022 to 15 January 2023. In the individual-level engagement analysis, we use these measures, while at the local authority-level we calculate the share of links that were clicked on at least once by summing the individual-level indicator *Brief opened* over all recipients in a local authority and dividing this by the number of recipients in that local authority. We construct this measure separately for every type of recipient, councillor, council officer, and media contact.

Lastly, we create another binary variable, *Engaged*, using information on email replies to our treatment. We record this engagement by manually classifying all emails we received between 19 October and 9 November 2022, using the header and body of the email to assess whether it represented a genuine human engagement. This classification excludes bouncebacks from emails that could not be delivered and auto-replies like out-of-office notifications or confirmation of reception.

To study heterogeneity in engagement at the councillor level we use information on the party affiliation of each councillor – and if available – of council officers. As the Oscar Research data does not provide information on a councillor's party affiliation, we use data from the Local Elections Archive Project (LEAP). The data spans all local elections in the UK from 2002 onwards and has information on the candidate name, council, ward, and party, as well as election outcomes. Using councillors' names, wards and councils, we match this dataset with the councillor-level Oscar Research data employing a Large Language Model. In cases where we observe the same councillor being affiliated with different parties, for instance because they switched parties, we keep only one councillor-party observation based on a random draw. Thus, each councillor's party affiliation can be interpreted as their party affiliation at a randomly selected point in time, acknowledging that this may not always reflect their most recent or longest-held affiliation. As we are interested only in the major parties, we code every councillor that does not belong to the Labour Party, Conservative Party, Liberal Democrats, Green Party, Independent Party, or UKIP as *Other party*.

Final datasets From these data sources, we construct different datasets for each part of the analysis – the estimation of the treatment effect on energy savings installations and the engagement analysis. To analyse the impact of the outreach on energy efficiency installations, we build five datasets that differ in the level of spatial aggregation. The first is at the Local Authority District (LAD) level, which represents local governments in the UK and is the unit of randomisation. The other four, which we use for robustness and mechanism analysis, are at lower spatial scales using statistical units called Output Areas (OA), Lower Layer Super Output Areas (LSOA), and Middle Layer Super Output Areas (MSOA). These are aggregations from UK census blocks that are constructed such that each area is approximately

comparable in terms of population size. OAs have an average population of 320 people, LSOAs of 1,700, and MSOAs of 8,200. Finally, we create a dataset at the property level. We use these datasets at a more granular spatial scale for two reasons. First, we analyse how robust our results are to different spatial levels. Second, we study how the treatment diffused from councillors to the general population. Both datasets are at the quarter-year level and have variables on treatment status and the number of energy efficiency installations in total and disaggregated by type of installation.

For the second part of the analysis, where we study who engages with the outreach, we have two datasets. One is at the LAD level and contains LAD characteristics discussed above, as well as engagement outcomes aggregated at the local authority level. The second dataset is at the councillor level to study individual responses to the outreach.

4 Effect of outreach on energy saving measures

In the first part of our analysis, we focus on the impact of the information treatment on the installation of energy-saving measures. We estimate five difference-in-differences regression models differing in the levels of fixed effects and the controls we include. The most basic regression model we run, which does not include any fixed effects, is the following:

$$y_{it} = \beta_0 + \beta_1 D_i + \beta_2 Post_t + \beta_3 (D_i \times Post_t) + \sum_{t=2021Q1}^{2024Q1} \gamma_t \tau_t \cdot \mathbf{X_i} + \epsilon_{it} \tag{1}$$

where we regress the outcome y_{it}, measuring the intensive and extensive margins of retrofitting installations of local authority i in quarter-year t, on the interaction of the treatment status D_i that equals one for a treated local authority i and zero otherwise, and a binary indicator $Post_t$ being one for every quarter-year t after the third quarter of 2022 when we sent out the emails. The coefficient of interest is β_1, which captures the causal effect of our information treatment on retrofitting installations after we sent out the treatment. As we observe a slight imbalance in terms of population and the number of Ukrainian refugees hosted, we flexibly control for interactions of these variables – captured by $\mathbf{X_i}$ – with quarter-year dummies

τ_t. Standard errors are clustered at the local authority level, the level of treatment assignment.

Table 1 presents the results of this regression. Additionally, column (2) controls for time-invariant differences across local authorities with local authority fixed effects. Column (3) includes strata fixed effects to evaluate only the variation within each stratum. Column (4) adds quarter-year fixed effects to control for any time-specific national shock. Column (5) allows for strata-specific time trends to account for strata-specific shocks. In both panels, the analysis is at the local authority level. In panel A, the dependent variable is the (log) number of total installations, while in panel B, we focus only on the total number of solar installations. We expect the effect to be driven by solar installations as these are the most common type of small-scale retrofit installations in the UK (MCS, 2026).

Across all columns in panel A, the estimated β_1 is similar in terms of size, positive, and statistically significant at the 10% significance level. These results suggest that informing local governments and local media about the expected costs of the energy crisis and the savings potential in their jurisdiction increases the number of retrofitting installations in treated authorities in the six quarters after the treatment was sent. The log number of installations increased by 0.0678 - 0.0763, implying an increase of roughly one additional installation in an average local authority. This translates into an increase of 7.02% - 7.9% over the mean.[8] Panel B shows the estimated coefficients for the same specification but with only solar PV installations as the outcome. The coefficients are even larger and still statistically significant.

We present further robustness exercises where we vary the level of spatial aggregation and the dependent variable, as well as event study plots in appendix tables A2 – A5 and appendix figures A2 – A3. Although it does not give us more variation in the treatment status, a finer spatial aggregation provides us more power by increasing the sample size. In terms of outcomes, we also examine an extensive margin measure equal to one if an area saw any new installation, which is more appropriate for finer aggregations, considering that installations are relatively rare

[8] As this regression is a log-linear specification, we obtain the percent increase by plugging in the estimated coefficients into the exponential function e^x.

at the neighbourhood level but not at the LAD level.[9] Overall, we find a consistent increase in installations in treated LADs and no evidence of pretrends.

As a further robustness check, we perform a randomisation inference exercise (Fisher, 1935; Rosenbaum, 2002). We re-randomise the treatment for 20,000 iterations to create a distribution of treatment effects and compare our true treatment to those. For each iteration, We re-estimate the most stringent specification from column (5) in Table 1 and extract the β_1 coefficient. Figure 1 shows the cumulative distribution function of these coefficients. The vertical line in red represents our true treatment effect. It intersects the cumulative distribution function of the placebo treatment effects at a value of 0.97. In other words, the effect we estimate for our true treatment lies within the top 5% of placebo treatments, reassuring us that it is not likely due to chance only.

Impact on Energy Consumption After looking at the effect of the information treatment on energy savings installations, it is natural to study energy consumption itself. We rely on the postcode-level data on energy consumption per domestic meter, which we aggregate to the local authority district level, at which we randomised our treatment. We run the same regression at the local authority level as in equation 1, with different sets of controls and fixed effects, just with energy consumption per meter as the dependent variable. Table A6 displays the resulting treatment effects of this regression and shows a very precise null-effect of our information treatment on energy consumption per meter.

Several mechanisms could help explain this null effect. First, there might be a rebound effect of solar panel adoption, whereby lower electricity bills increase household demand via an income effect. (Aydın et al., 2023). Second, the aggregate energy-consumption data do not reveal whether energy generated by newly installed solar PV systems is consumed by the installing household or exported to the grid. Consequently, an increase in local solar PV generation need not produce a detectable change in measured LAD-level domestic energy consumption. Finally,

[9]For the LAD level analysis, we present only the estimated coefficients for the regression with the intensive margin outcomes, that is the logarithm of total and solar installations. There is little variation in the binary outcome across LADs, as virtually every LAD saw a new retrofit/solar installation in a given quarter. For the LSOA level regressions, we present four event study graphs for the two types of installations (total and solar only) and the two margins (extensive and intensive).

the savings implied by our estimates on solar-panel installations are relatively small. We observe one additional installation in a quarter after the treatment happened. An average solar PV system working at peak capacity generates 3,700 kWh of electricity per year, that is 925 kWh per quarter (MCS, 2026). Given that there are about 80,000 properties in an average LAD, the electricity saving effect that we would be able to detect amounts to 0.011 kWh per property.

5 Who engages with the information treatment?

In this section, we study the determinants of engaging with our information brief. This analysis is correlational.

Council-level evidence We create a council-level dataset to correlate local engagement with local authority characteristics. At the council level, we measure engagement with the share of briefs opened. We construct this measure for each recipient type, i.e. councillors, council officials, and media contacts. Then we run the following regression

$$EmailsRead_c = \alpha + \mathbf{X_c}'\beta + \varepsilon_c \tag{2}$$

where $\mathbf{X}$ is a vector of covariates that includes binary indicators for savings potential below median and EPC coverage below median, population, household income, ownership share, share of Ukrainians hosted, whether there was an election in 2023, and binary indicators for conservative council control, labour council control, and other council control where the left out category is no overall council control. We can perform this analysis only for the subsample of treated local authorities.

Table 2 presents the results of this analysis. Two clear overall patterns of engagement at the council level emerge. First, average household income in the local authority is negatively related to the total share of briefs opened, overall and separately by councillors and council officials. A one standard deviation increase in average household income is associated with a decrease of 15 and 12 percentage points in the share of briefs opened by politicians and council employees, respec-

tively. Second, the share of Ukrainians who migrated to a local authority after the Russian invasion of Ukraine is positively and statistically significantly related to the engagement of recipients with the information brief in that authority.

Councillor-level evidence At the councillor level, we compiled a dataset using information on engagement outcomes from our email replies and log files, combined with data on party affiliation and overall council control. In this analysis, we regress the three engagement variables measuring the extensive margin of opening the brief, the intensive margin of the number of clicks on the brief, and a binary measure of contacting us on indicator variables of party affiliation. The reference category is Conservative party members.

Table 3 presents the results of these regressions. On the extensive margin, only independent councillors are significantly more likely to read the email than conservative councillors, by a margin of 5 percentage points. For all the other parties, there are no statistically significant differences in the propensity to read the brief in the first place. On the intensive margin, we observe more statistically significant differences. Councillors from the Labour party and councillors from the Liberal Democrats party read the information brief significantly more often than Conservative councillors by 0.11-0.12 times, which represents an increase of 18-19% over the mean. Members of the Green party read the brief even more, 0.28 more times than Conservative councillors, representing an increase of 45% over the mean. Lastly, members of the Liberal Democrats and of the Greens were statistically significantly more likely to reply to our outreach treatment, by 0.8 percentage points and 2.5 percentage points, respectively. Given that the average response rate was 0.005 these are large differences translating into an increase of 150% for Liberal Democrats and 460% for Greens.[10] These patterns are in line with results from Senninger and Seeberg (2024), who find that politicians from a right-leaning political block in Denmark are less likely to engage with information on climate action.

[10] Additionally, we run this exercise splitting the sample into council control by Labour and Tory in appendix table A7. The results confirm the findings here but uncover an interesting source of heterogeneity, namely that Labour party members appear less likely to open our brief in Conservative-controlled councils.

6 How does the information treatment diffuse from politicians to the population?

So far, the question remains as to how our treatment, which targeted politicians, council workers, and media, led to households undertaking retrofits. One hypothesis is that these individuals talked to their neighbours after reading the brief, spreading information on the benefits of retrofitting. Similarly, treatment may be more likely to diffuse through other channels where councillors live. For example, households living near councillors may be more attentive to council politics, more connected to local civic or party networks, or more likely to receive information through neighbourhood groups, local media, or online communication, and thus be more likely to learn about the information contained in our treatment.

To test the local-diffusion hypothesis, we conduct a heterogeneity analysis using information on councillors' home addresses and their party affiliation. We start with a list of councillors' residential postcodes and link them to 2021 Output Areas (OAs) using the official postcode to geography lookup. This allows us to aggregate the councillors' residences to our main analyses' units of observation. Our main variables of interest are an indicator equal to one if at least one councillor lives in the area (extensive margin) and a count of the number of resident councillors (intensive margin). However, these effects might not stop at the border of an OA. To consider whether the local exposure spills over to neighbouring areas, we construct three spillover variables: an indicator variable for whether at least one neighbouring OA is home to a councillor, an intensive margin variable counting the number of adjacent OAs with resident councillors, and the share of neighbouring OAs with councillor residences.

We then estimate the following regression.

$$\begin{aligned} Y_{iat} = \beta_1 \big(\text{Post}_t \times \text{Treat}_a \times C_i\big) + \beta_2 \big(\text{Post}_t \times \text{Treat}_a \times S_i\big) \\ + X'_{at}\gamma + \alpha_i + \lambda_{\text{Treat}_a t} + \mu_{C_i t} + \nu_{S_i t} + \varepsilon_{iat}. \end{aligned}$$

where the outcome is an indicator capturing whether we observe any new retrofit installations in small area i, authority a, and quarter-year t and the main regression of interest is a triple interaction of the treatment indicator, the post indicator, and one of the councillor residence measures C_i. To capture spillovers,

we include another triple interaction of treatment indicator, post indicator and the spillover variable S_i. In addition, we include small-area fixed effects, as well as treatment-by-quarter-year fixed effects to control for common time trends across all treated units, and councillor-residence-by-quarter-year fixed effects, which alleviate concerns that councillors live in richer areas that, in general, have more resources to install retrofit upgrades. The coefficient of interest β_1 captures whether OAs in treated authorities with a resident councillor saw a different post-intervention change in retrofit installations than OAs in treated authorities without one. Lastly, we again include the interactions of quarter-years with population and the number of Ukrainian refugees as control variables. β_2 captures whether treatment effects extend beyond councillor residence areas into neighbouring OAs.

We present the results of this regression in table 4, where we vary the spillover variables across the three columns. The results show a statistically significant effect in two out of three specifications for the councillor residence triple interaction. This implies that neighbourhoods in treated local authorities that are home to a politician saw an increase in the likelihood of an additional retrofit installation after the treatment compared to those areas which are not home to a councillor. In particular, this effect is double the effect seen in the rest of the local authority. Interestingly, on all three spillover variables, the coefficients are small and statistically insignificant. If anything, the effect in neighbouring areas seems to be negative. This reinforces the interpretation that our information treatment played out at a highly local spatial scale, potentially clustering only around the treated councillors' own homes. The concentration of additional retrofits near councillors' homes is consistent with local diffusion. While councillors' residential locations are not randomly assigned, our specification controls for small area fixed effects and councillors' residence area time trends, thus assuaging heterogeneity concerns.

7 Conclusion

In this paper, we study if and how locally tailored information sent to local political actors increases their constituencies' energy efficiency. We carried out an information intervention in November 2022, providing local councillors, council workers,

and local media outlets with tailored evidence on the distributional impact of the energy crisis and how retrofitting homes in their authority can help to cushion the effects of this shock. Using a randomised field experiment across local authorities in England and Wales, we find that treated authorities see a significant increase in retrofit installations. We do not find any impact on energy consumption. The effects are highly localised around councillors' residential addresses.

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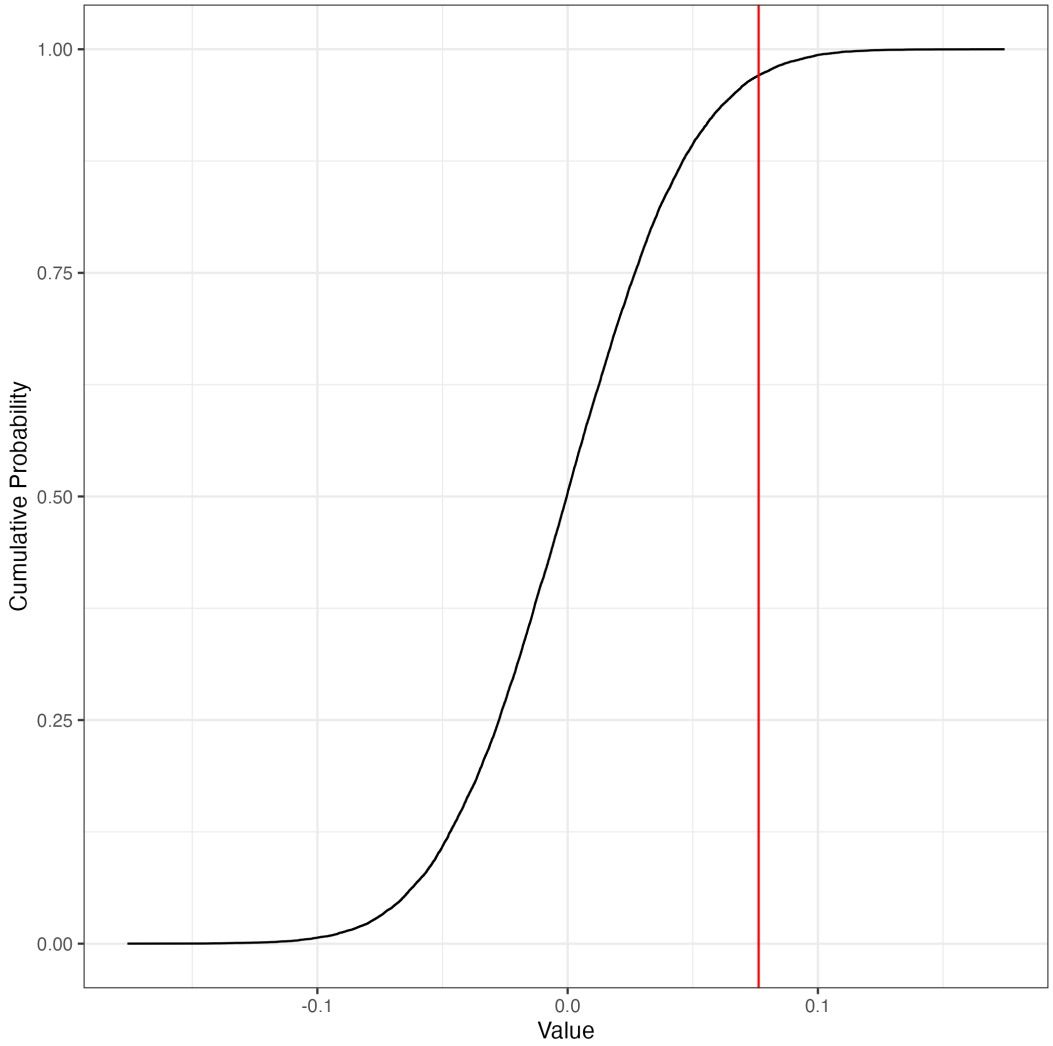
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Figures

Figure 1: Permutation test of treatment



Notes: The figure plots the cumulative distribution function of the treatment effects of a permutation test with 20,000 iterations. For each iteration, we create a random "placebo" treatment and run a regression corresponding to the regression in panel A of table 1 column (5), i.e. we include LAD, strata, and strata × quarter - year fixed effects. The red vertical line represents the "true" estimated treatment effect with the true randomisation.

Tables

Table 1: Effect of treatment on installations - LAD level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	0.075*	0.085*	0.085*	0.071*	0.083**
	(0.041)	(0.044)	(0.044)	(0.041)	(0.040)
Dependent variable mean	4.25	4.25	4.25	4.25	4.25
Observations	3,766	3,766	3,766	3,766	3,766
Panel B: log(solar installation)					
Post × Treatment	0.097**	0.099**	0.099**	0.079*	0.084*
	(0.046)	(0.050)	(0.050)	(0.044)	(0.044)
Dependent variable mean	3.97	3.97	3.97	3.97	3.97
Observations	3,763	3,763	3,763	3,763	3,763
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Controls include the interaction of quarter-year dummies with population and with the number of Ukrainian refugees arrived. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 2: **Engagement by recipient and by LAD characteristic**

	(1)	(2)	(3)	(4)
	Briefs opened			
	All	Councillor	Council officer	Media
Sav. pot < med.	0.019	0.163	0.178	0.011
	(0.034)	(0.123)	(0.116)	(0.031)
EPC cov. < med	-0.024	-0.092	-0.170	-0.027
	(0.033)	(0.116)	(0.110)	(0.030)
Population	-0.048*	-0.095	-0.118	0.034
	(0.027)	(0.097)	(0.092)	(0.024)
HH income	-0.051**	-0.150**	-0.124*	0.006
	(0.021)	(0.073)	(0.070)	(0.020)
Ownership	-0.173	-0.977	-0.490	-0.111
	(0.189)	(0.676)	(0.641)	(0.171)
Ukrainians	0.0004**	0.001*	0.001**	-1.56×10^{-5}
	(0.0002)	(0.0006)	(0.0006)	(0.0001)
Election 2023	-0.005	-0.004	0.009	0.005
	(0.036)	(0.130)	(0.123)	(0.033)
Conservative council	0.029	-0.194	-0.237*	0.021
	(0.040)	(0.141)	(0.134)	(0.036)
Labour council	-0.006	-0.064	-0.131	-0.009
	(0.046)	(0.164)	(0.156)	(0.042)
Other control council	0.084	0.041	0.107	0.047
	(0.053)	(0.191)	(0.181)	(0.049)
cons	Yes	Yes	Yes	Yes
Dependent variable mean	0.167	0.565	0.629	0.082
Observations	156	156	156	127

Notes: This table shows the results of multivariate regressions that measure the engagement of local authority districts (LAD) with our policy brief by different LAD characteristics. The dependent variable is the share of briefs opened in the aggregate (All) and by the three recipient types: Councillor, Council Officer, and Media. The measure is calculated by dividing the number of times a policy brief recipient clicked on the link using information from log files by the amount of emails which were sent to recipients within a LAD. The sample is restricted to only treatment LADs. For the analysis on media recipients only, the sample is even smaller, as we don't have media contacts for every local authority. For control LADs this measures are zero. The explanatory variables are the following: There are energy related variables like the savings potential as calculated in Fetzer, Gazze, and Bishop (2022), the energy price certificate coverage as well as indicators for being below the median savings potential or EPC coverage. Furthermore, we control for LAD characteristics like population, average household income, ownership rate, the number of Ukrainian refugees an LAD received, and whether there are local elections in 2023. The variables savings potential, population and household income are standardised by dividing each variable by its standard deviation. In addition we add controls for the party controlling the LADs council. The left-out reference category is "no overall control council". Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 3: Engagement of councillor by party affiliation

	(1)	(2)	(3)
	Brief opened	Clicks	Engaged
Labour	0.021	0.110***	0.002
	(0.013)	(0.029)	(0.002)
Libdem	0.020	0.121***	0.009***
	(0.017)	(0.037)	(0.002)
Green	0.049	0.278***	0.025***
	(0.030)	(0.066)	(0.004)
UKIP	0.039	0.310	-0.002
	(0.134)	(0.289)	(0.019)
Independent	0.054**	0.016	0.003
	(0.022)	(0.047)	(0.003)
Other party	-0.042	-0.032	0.003
	(0.027)	(0.059)	(0.004)
Dependent variable mean	0.474	0.609	0.005
Observations	8,208	8,208	8,208

Notes: This table presents the results from multivariate regressions. The dependent variables capture the engagement of a councillor on the extensive and intensive margin. Column (1) measures the extensive margin whether a councillor read the brief. This is a binary measure that is one if we record either one or more clicks in the log files or the recipient replied to us by email confirming the reception of the brief. Column (2) measures the intensive margin of engagement by calculating the number of times a recipient clicked on the brief. Column (3) also measures an extensive engagement margin by measuring whether a councillor got into contact with us by replying to our email brief. The outcome measures are regressed on dummy variables indicating the party affiliation of the councillor. This information is taken from the Local Elections Archive Project (LEAP) which is kindly collected by Andrew Teale. The sample is restricted to councillors for which we could find information on the party affiliation. The omitted party affiliation is the conservative party. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p $<$0.01, ** p $<$0.05, and * p $<$0.1.

Table 4: Effect of treatment on installations by councillor residence and spillovers – Output Area (OA) level

	(1)	(2)	(3)	(4)
Dependent variable: $\mathbb{1}$(New Installations)				
Post × Treatment	-0.011*			
	(0.006)			
Post × Treatment × Own councillor	0.022*	0.022*	0.022*	0.022
	(0.013)	(0.013)	(0.013)	(0.013)
Post × Treatment × Spillover (any)	-0.003	-0.003		
	(0.008)	(0.008)		
Post × Treatment × Spillover (count)			-0.003	
			(0.006)	
Post × Treatment × Spillover (share)				-0.009
				(0.035)
Dependent variable mean	0.099	0.099	0.099	0.099
Observations	3,011,800	3,011,800	3,011,800	3,011,800
Regression specification:				
Area FE	X	X	X	X
Treatment x Quarter-year FE		X	X	X
Councillors Residence x Quarter-year FE	X	X	X	X
Spillover x Quarter-year FE	X	X	X	X
Controls	X	X	X	X

Notes: This table shows the results of four multivariate regressions from equation 6. The unit of analysis is an Output Area (OA). The dependent variable in all four regressions is an indicator equal to one for whether an OA gets an additional retrofit installation in a quarter-year. Own councillor is an indicator equal to one if a councillor lives in the area. Spillover (any) is an indicator equal to one if an area neighbors a councillor residence area. Spillover (count) counts the number of neighbouring areas with a resident councillor. Spillover (share) is the share of all neighbouring areas that are residence of a councillor. Standard errors in parentheses are clustered at the district level. Columns (2) - (4) include treatment x quarter-year fixed effects, while in column (1) we include the treatment x post interaction. Stars indicate *** p <0.01, ** p <0.05, and * p <0.1.

Appendix to "Weathering the Energy Crisis: Can Tailored Information to Local Governments Spur Climate Action?"

For Online Publication

A Appendix figures

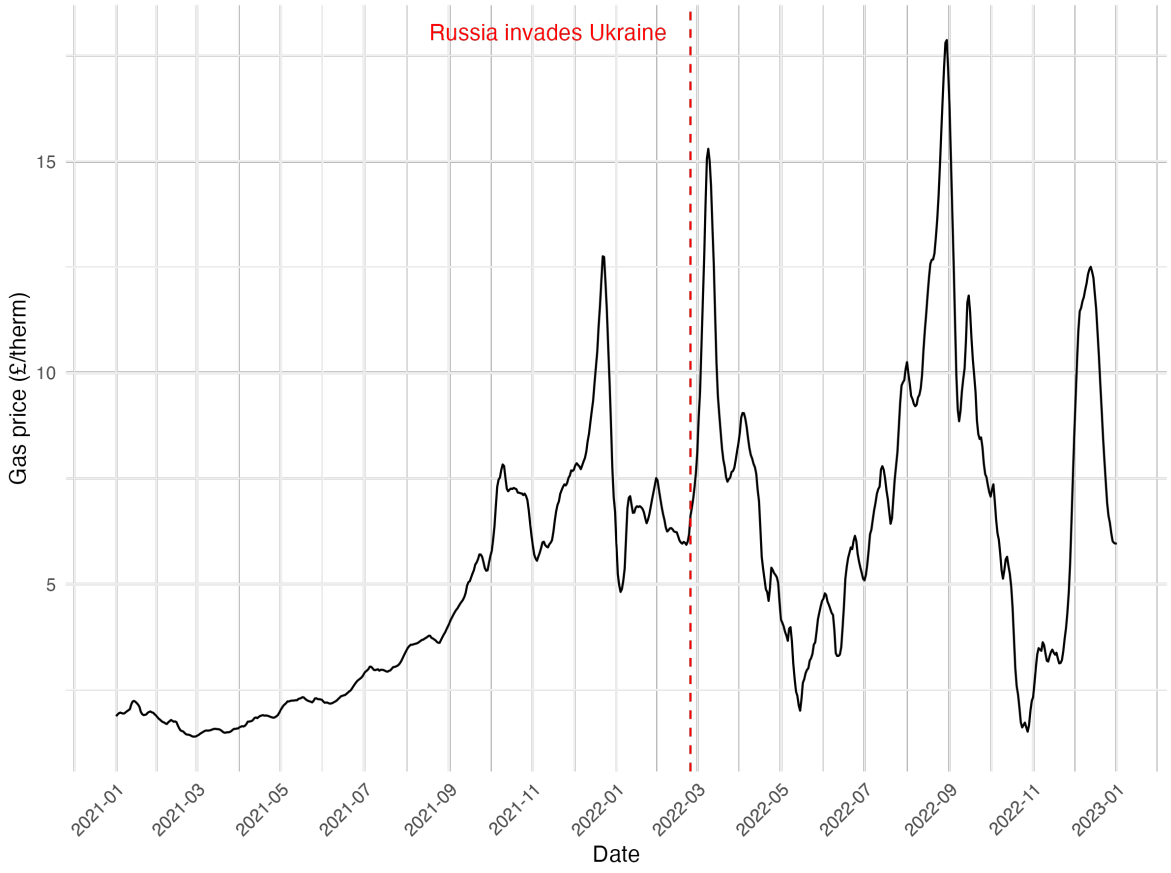
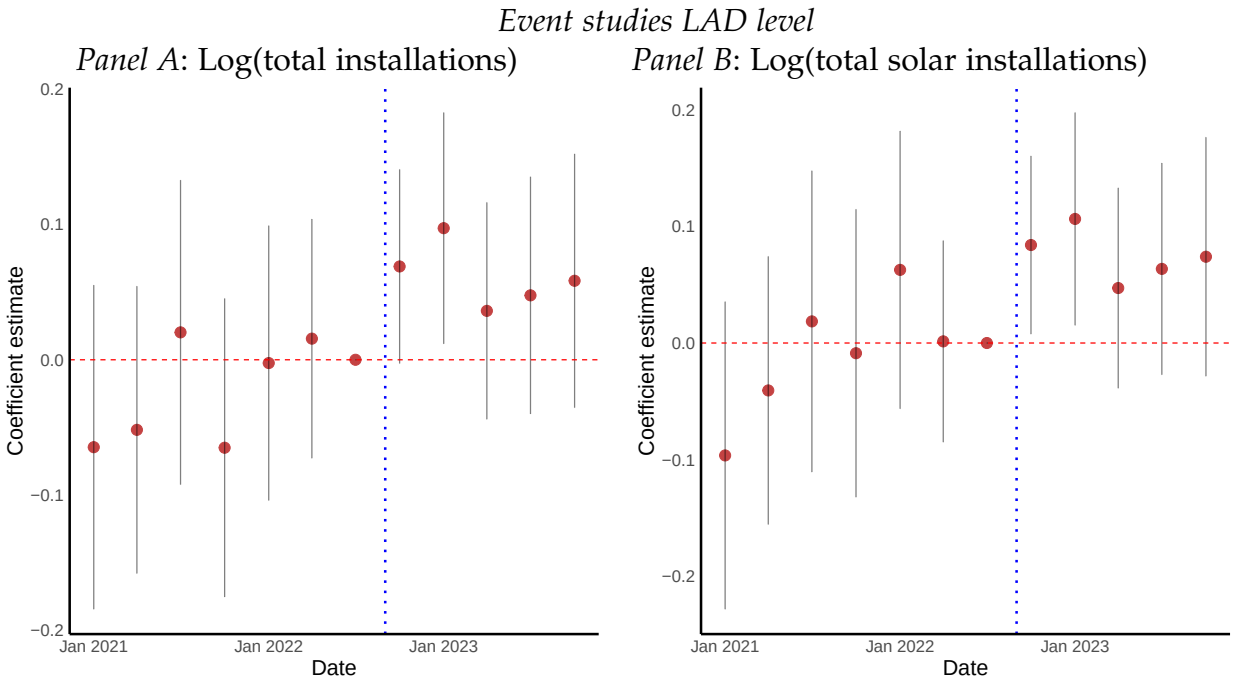


Figure A1: Gas prices around the Russian invasion of Ukraine

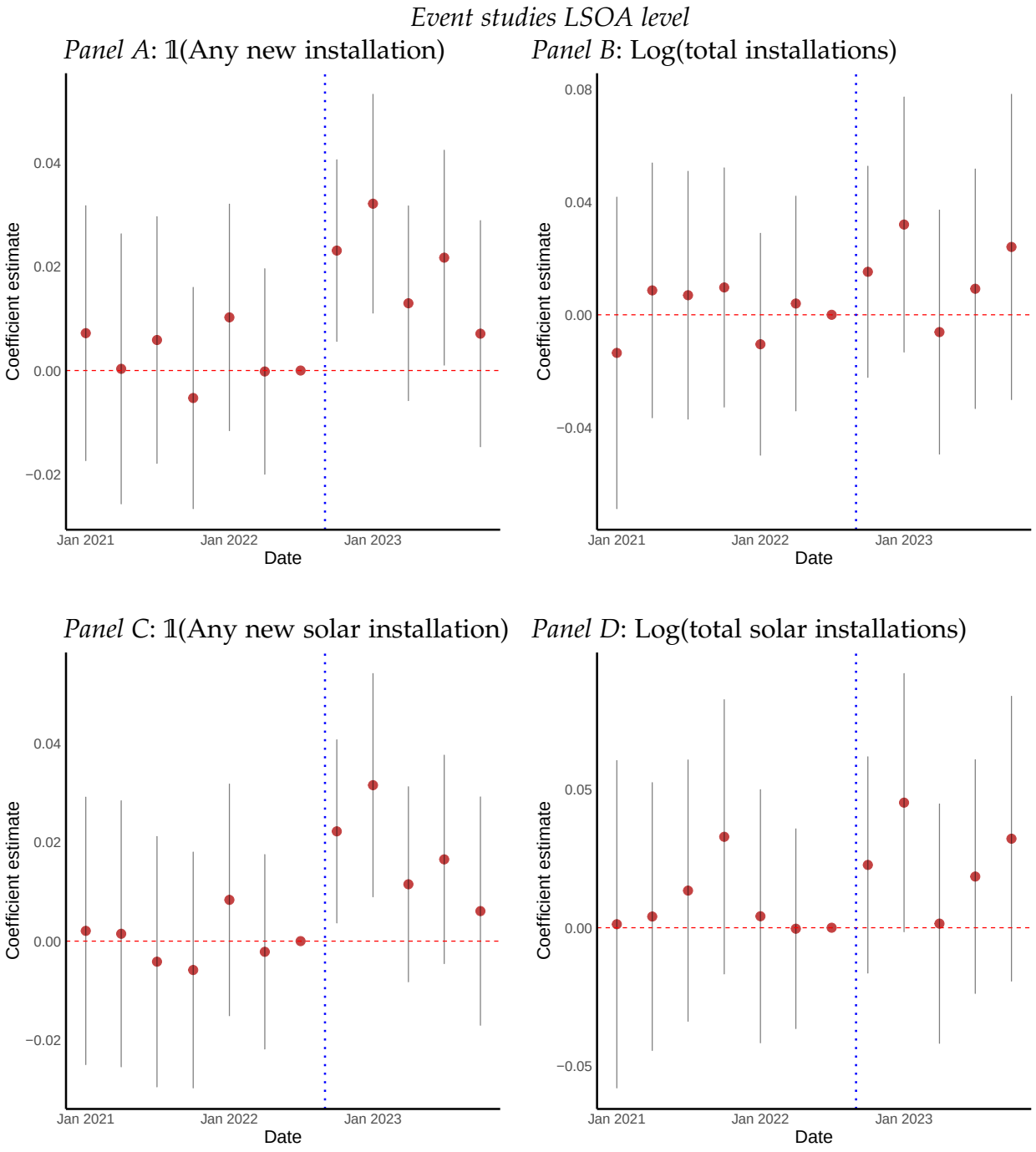
Notes: The graph shows monthly gas prices in England in £ per kilowatt hours for 2021-2023. Source: Office for National Statistics.

Figure A2: Event studies LAD level, quarterly data



Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a UK local authority (LAD). The dots depict point estimates and the bars 90% confidence intervals. We present here only the estimated coefficients for the regression with the intensive margin outcome. There is little variation in the binary outcome across LADs, as virtually every LAD saw a new retrofit/solar installation in a given quarter.

Figure A3: Event studies LSOA level, quarterly data



Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a UK lower layer super output area (LSOA). The dots depict point estimates and the bars 90% confidence intervals.

B Appendix tables

Table A1: Randomisation Balance

Variable	Treatment	Control	P-Value
Has Media Contact	0.824 (0.382)	0.866 (0.342)	0.378
Election in 2023	0.626 (0.485)	0.544 (0.5)	0.197
Media at Lower Spatial Resolution	0.291 (0.456)	0.311 (0.464)	0.857
In England	0.933 (0.25)	0.933 (0.251)	0.903
Savings Potential below Median	0.491 (0.501)	0.512 (0.501)	0.944
EPC Coverage below Median	0.521 (0.501)	0.481 (0.501)	0.515
Average HH Income in 2023	43696 (7725)	43924 (7841)	0.998
Population	63264 (37826)	74854 (51434)	0.033
Ownership Rate	0.682 (0.107)	0.663 (0.106)	0.373
# Ukranian Refugees	200.576 (146.083)	238.866 (186.434)	0.061
Conservative Council	0.38 (0.487)	0.363 (0.482)	0.735
Labour Council	0.233 (0.424)	0.256 (0.438)	0.947
No Overall Control in Council	0.288 (0.454)	0.256 (0.438)	0.702
Other Party Control in Council	0.098 (0.298)	0.125 (0.332)	0.344
Total installations in pre-treatment year	325.9 (269.8)	354.5 (305.4)	0.369
Solar installations in pre-treatment year	246.7 (194.3)	266.8 (217.8)	0.378
N	165	164	

Notes: The table reports means and standard deviations of selected characteristics among treatment and control councils. P-values test the treatment coefficient in regressions controlling for the other stratification indicators.

Table A2: Effect of treatment on installations - MSOA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	0.021	0.031	0.031	0.022	0.040
	(0.038)	(0.039)	(0.039)	(0.035)	(0.029)
Dependent variable mean	1.32	1.32	1.32	1.32	1.32
Observations	63,851	63,851	63,851	63,851	63,851
Panel B: log(solar installation)					
Post × Treatment	0.050	0.045	0.045	0.036	0.050
	(0.045)	(0.043)	(0.043)	(0.041)	(0.036)
Dependent variable mean	1.17	1.17	1.17	1.17	1.17
Observations	60,335	60,335	60,335	60,335	60,335
Panel C: 𝟙(any new installation)					
Post × Treatment	0.188*	0.253**	0.253**	0.260**	0.237**
	(0.096)	(0.109)	(0.109)	(0.112)	(0.101)
Dependent variable mean	0.800	0.722	0.722	0.722	0.721
Observations	85,764	61,308	61,308	61,308	61,094
Panel D: 𝟙(any new solar installation)					
Post × Treatment	0.181*	0.231**	0.231**	0.238**	0.235**
	(0.097)	(0.106)	(0.106)	(0.108)	(0.099)
Dependent variable mean	0.756	0.704	0.704	0.704	0.703
Observations	85,764	69,936	69,936	69,936	69,684
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Controls include the interaction of quarter-year dummies with population and with the number of Ukrainian refugees arrived. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A3: Effect of treatment on installations - LSOA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	0.009	0.007	0.007	0.006	0.014
	(0.022)	(0.024)	(0.024)	(0.024)	(0.018)
Dependent variable mean	0.603	0.603	0.603	0.603	0.603
Observations	156,645	156,645	156,645	156,645	156,645
Panel B: log(solar installation)					
Post × Treatment	0.020	0.011	0.011	0.011	0.018
	(0.025)	(0.024)	(0.024)	(0.024)	(0.020)
Dependent variable mean	0.515	0.515	0.515	0.515	0.515
Observations	139,748	139,748	139,748	139,748	139,748
Panel C: 𝟙(any new installation)					
Post × Treatment	0.070	0.097	0.097	0.099	0.121**
	(0.045)	(0.069)	(0.069)	(0.070)	(0.060)
Dependent variable mean	0.411	0.414	0.414	0.414	0.414
Observations	412,116	381,084	381,084	381,084	381,084
Panel D: 𝟙(any new solar installation)					
Post × Treatment	0.088*	0.116	0.116	0.120	0.139**
	(0.051)	(0.073)	(0.073)	(0.074)	(0.065)
Dependent variable mean	0.366	0.386	0.386	0.386	0.386
Observations	412,116	384,960	384,960	384,960	384,960
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Controls include the interaction of quarter-year dummies with population and with the number of Ukrainian refugees arrived. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A4: Effect of treatment on installations - OA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	-0.0009	-0.0051	-0.0051	-0.0033	0.0058
	(0.0141)	(0.0160)	(0.0160)	(0.0161)	(0.0098)
Dependent variable mean	0.28885	0.28885	0.28885	0.28885	0.28885
R^2	0.02680	0.47634	0.47634	0.48943	0.49623
Observations	267,375	267,375	267,375	267,375	267,375
Panel B: log(solar installation)					
Post × Treatment	0.0089	0.0038	0.0038	0.0059	0.0100
	(0.0111)	(0.0106)	(0.0106)	(0.0108)	(0.0091)
Dependent variable mean	0.23739	0.23739	0.23739	0.23739	0.23739
R^2	0.01885	0.50522	0.50522	0.52407	0.52844
Observations	226,135	226,135	226,135	226,135	226,135
Panel C: 𝟙(any new installation)					
Post × Treatment	0.0476	0.0494	0.0494	0.0504	0.0813*
	(0.0393)	(0.0512)	(0.0512)	(0.0516)	(0.0439)
Dependent variable mean	0.13803	0.20079	0.20079	0.20079	0.20079
Observations	1,937,100	1,329,372	1,329,372	1,329,372	1,329,372
Panel D: 𝟙(any new solar installation)					
Post × Treatment	0.0679	0.0735	0.0735	0.0754	0.1063**
	(0.0478)	(0.0600)	(0.0600)	(0.0607)	(0.0523)
Dependent variable mean	0.11674	0.17890	0.17890	0.17890	0.17890
Observations	1,937,100	1,262,772	1,262,772	1,262,772	1,262,772
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A5: Effect of treatment on installations - Property level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	-0.0124	-0.0076	-0.0076	-0.0085	-0.0008
	(0.0092)	(0.0109)	(0.0109)	(0.0106)	(0.0103)
Dependent variable mean	0.10256	0.10256	0.10256	0.10256	0.10256
R^2	0.05792	0.95459	0.95459	0.95738	0.95827
Observations	367,449	367,449	367,449	367,449	367,449
Panel B: log(solar installation)					
Post × Treatment	-0.0035	-0.0247	-0.0247	-0.0299	-0.0078
	(0.0027)	(0.0224)	(0.0224)	(0.0226)	(0.0212)
Dependent variable mean	0.07092	0.07092	0.07092	0.07092	0.07092
R^2	0.03420	0.96161	0.96161	0.96323	0.96597
Observations	300,781	300,781	300,781	300,781	300,781
Panel C: 𝟙(any new installation)					
Post × Treatment	0.0667	0.0711	0.0711	0.0713	0.0960**
	(0.0444)	(0.0478)	(0.0478)	(0.0479)	(0.0430)
Dependent variable mean	0.02106	0.08731	0.08731	0.08731	0.08731
Observations	17,444,100	4,208,376	4,208,376	4,208,376	4,208,376
Panel D: 𝟙(any new solar installation)					
Post × Treatment	0.0950*	0.1009*	0.1009*	0.1015*	0.1307**
	(0.0544)	(0.0584)	(0.0584)	(0.0587)	(0.0537)
Dependent variable mean	0.01724	0.08475	0.08475	0.08475	0.08475
Observations	17,444,100	3,549,108	3,549,108	3,549,108	3,549,108
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A6: Effect of treatment on energy consumption - LAD level, annual data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(energy consumption per meter)					
Post × Treated	-0.0002	-0.0002	-0.0002	-0.0002	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dependent variable mean	9.55	9.55	9.55	9.55	9.55
Observations	1,495	1,495	1,495	1,495	1,495
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Year FE				X	
Strata x Year FE					X
Controls	X	X	X	X	X

Notes: This table shows the effect of the information treatment on log energy consumption. Energy consumption is measured as combined electricity and gas consumption divided by the number of meters in a Local Authority District. *** p <0.01, ** p <0.05, and * p <0.1.

Table A7: Engagement of councillor by party affiliation and council control

	(1)	(2)	(3)	(4)	(5)	(6)
Council control	Labour			Conservative		
	Brief opened	Clicks	Engaged	Brief opened	Clicks	Engaged
Conservative	-0.028	0.049	-0.006			
	(0.030)	(0.085)	(0.005)			
Libdem	0.232***	0.185	0.018**	0.080***	0.171***	0.006
	(0.055)	(0.156)	(0.009)	(0.028)	(0.051)	(0.004)
Green	0.145	-0.091	0.066***	-0.014	0.148*	0.005
	(0.095)	(0.267)	(0.015)	(0.045)	(0.083)	(0.006)
Independent	0.145***	-0.013	-0.006	0.106***	0.070	0.016***
	(0.053)	(0.149)	(0.009)	(0.040)	(0.073)	(0.005)
Other party	0.103	0.860***	0.038**	-0.042	-0.060	-0.003
	(0.104)	(0.294)	(0.017)	(0.054)	(0.099)	(0.007)
Labour				-0.067**	0.071	-0.003
				(0.028)	(0.051)	(0.004)
UKIP				-0.073	0.707*	-0.003
				(0.201)	(0.366)	(0.026)
Dependent variable mean	0.422	0.507	0.005	0.411	0.499	0.004
Observations	1,998	1,998	1,998	3,009	3,009	3,009

Notes: This table presents the results from multivariate regressions. The dependent variables capture the engagement of a councillor on the extensive and intensive margin. Columns (1) and (4) measure the extensive margin whether a councillor opened the brief. This is a binary measure that is one if we record either one or more clicks in the log files or the recipient replied to us by email confirming the reception of the brief. Columns (2) and (5) measure the intensive margin of engagement by calculating the number of times a recipient clicked on the brief. Columns (3) and (6) also measure an extensive engagement margin by measuring whether a councillor got into contact with us by replying to our email brief. The outcome measures are regressed on dummy variables indicating the party affiliation of the councillor. We split the sample by council control into Labour- and Conservative-controlled councils. This information is taken from the Local Elections Archive Project (LEAP), which is kindly collected by Andrew Teale. The sample is restricted to councillors for which we could find information on the party affiliation. The omitted party affiliation is the party in power. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

C Example of treatment outreach

C.1 Email to Darlington

Subject: New Research: How will the energy crisis affect households in Darlington?
Date: Tuesday, 25. October 2022 at 19:46:43 Central European Summer Time
From: Fetzer, Thiemo on behalf of energycrisis, resource
To: FELD, IMMANUEL (PGR)
Attachments: PNG image.png, PNG image.png

How will the energy crisis affect households in Darlington?

Dear Mr. Feld,

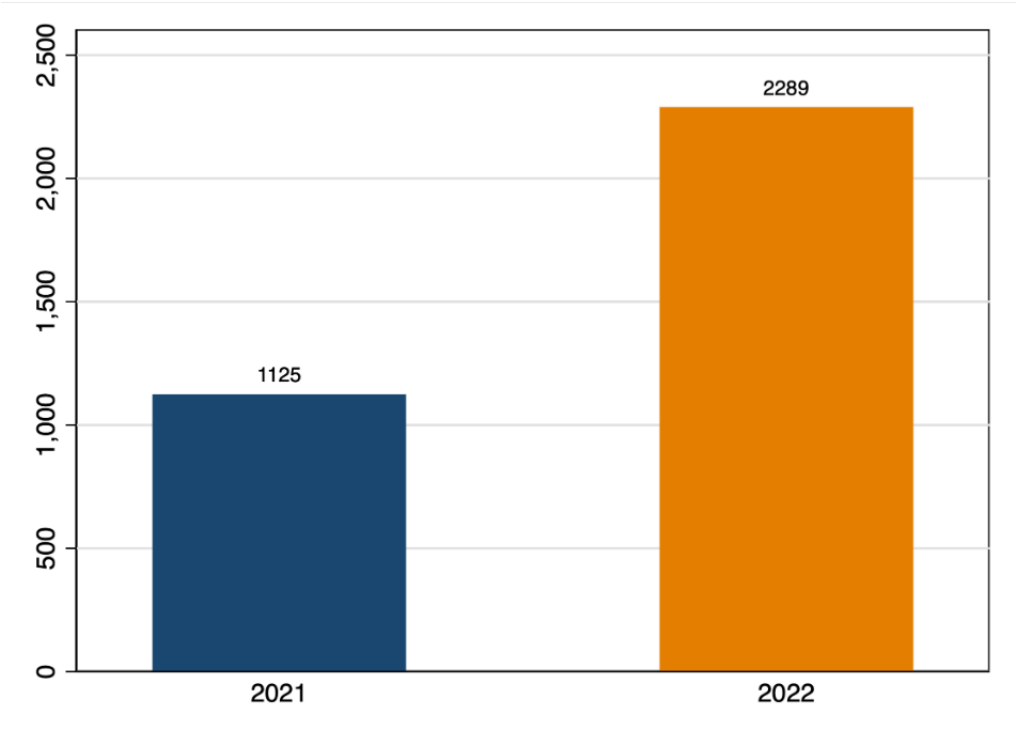
We are a group of economists at the University of Warwick who have analysed the impacts of the energy crisis for Darlington. Our data analysis **specific to Darlington**, along with more detail is available here:

https://warwick.ac.uk/fac/soc/economics/staff/lagazze/energycrisis/brief_district_e06000005.pdf.

The energy crisis is a **broad-based economic shock** that can threaten social and economic stability in the UK. Households in Darlington will be **hit hard**. Even with government support through the Energy Price Guarantee, we estimate that households in Darlington will see **an increase in their energy bills by, on average, £1164** relative to energy prices from October 2021.

This is an economic shock that affects **all households in Darlington**, even households who consume very little energy, which may threaten the social and economic stability in this country and your community.

Figure 1: Impact of energy crisis on households in Darlington: Increase in annual average energy bills

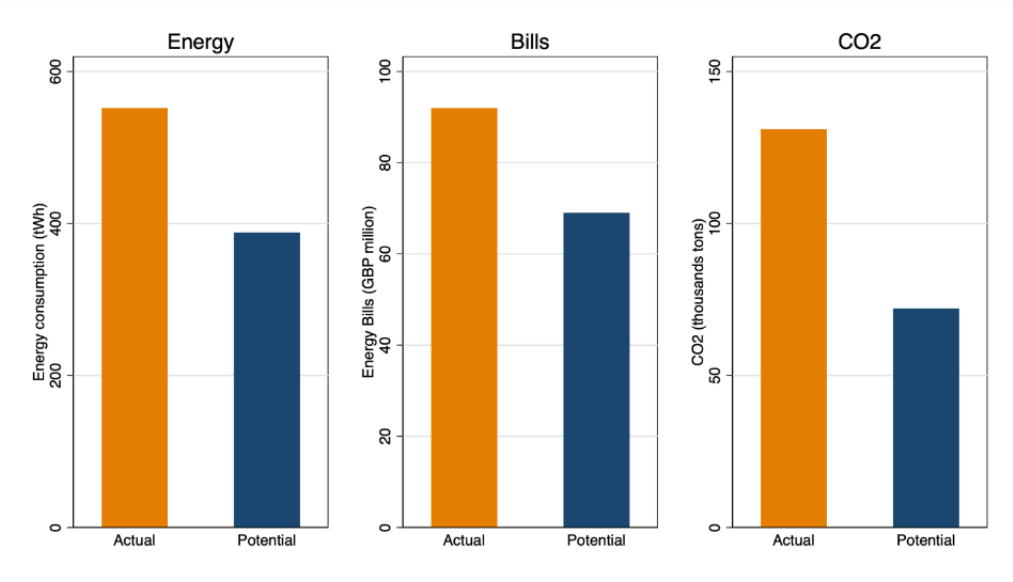


Government intervention, for example through the **Energy Price Guarantee** may **temporarily reduce the burden** on households, but ultimately, the higher price for energy will be paid either by households directly, or indirectly, through the government, which needs to **raise taxes, cut spending or borrow** in order to cover the cost.

But there is another alternative: to **save energy**. And the savings potential in Darlington is large. We estimate that all households in Darlington combined could save **more than £23 million in energy bills per year** at current market prices. In fact, if homes for which we do not have data are comparable to those for which we do have data, financial savings could be as high as £36 million per year.

This savings potential exists because we estimate that the residential building stock in Darlington could save up to **30% of its primary energy consumption** if buildings were **properly insulated**. We estimate that the building stock in Darlington alone could save at least **60000 tons of CO2 per year**. The CO2 savings themselves have a monetary value: at present emissions trading prices of £78 per ton of CO2, we estimate that the 60000 tons of CO2 emissions that could be saved are worth £4.7 million per year.

Figure 2 – Energy, financial and CO2 savings potential in Darlington's building stock



Helping households insulate their properties could be a win-win-win as households could **permanently save money**; it would support the **fight against the climate crisis** and it could help reduce our **vulnerability to foreign powers** that may use energy as leverage or as a weapon in a hybrid war.

With the crisis unfolding, households may feel helpless and even more disconnected from the central government. Yet, our research highlights that empowering households to unlock the savings potential in their own homes is key to their wellbeing and to the country's decarbonisation goals.

Therefore, it is imperative for local government and local councils to devise ways to ensure that the existing schemes reach households. Our team will be happy to assist in identifying barriers to take-up of energy efficiency investments, in designing programs to overcome these barriers, and in finding out "what works". Such a partnership can make your district an

example to follow in the whole country.

We have prepared more **analysis specific to Darlington** that is available as a brief *here*.

Thiemo Fetzer
Ludovica Gazze
Menna Bishop

University of Warwick
CAGE Research Centre

C.2 Brief to Darlington

How will the energy crisis affect households in UK districts?

Thiemo Fetzer, Ludovica Gazze, Menna Bishop (University of Warwick, *energycrisis@warwick.ac.uk*.)

25 Oct 2022

The energy crisis in Darlington: Executive Summary

This report provides a summary of research that is carried out at by economists at the University of Warwick. We have modelled what the impact of the energy crisis is going to be across households in England and Wales and have developed this specific brief for Darlington. We find that the **average household in Darlington may see increases in energy bills of £1164 per year**, even with the existing government support in place through the Energy Price Guarantee (EPG). Without the EPG, average energy bills would increase **by as much as £2036** when measuring prices as per the Ofgem October announced prices. Naturally, the difference between the cost increase that households face vis-à-vis the market prices of energy will need to be paid somehow by the government, which invariably means **higher taxes, lower public spending or more public debt**. The shock is broad based and will virtually affect all households.

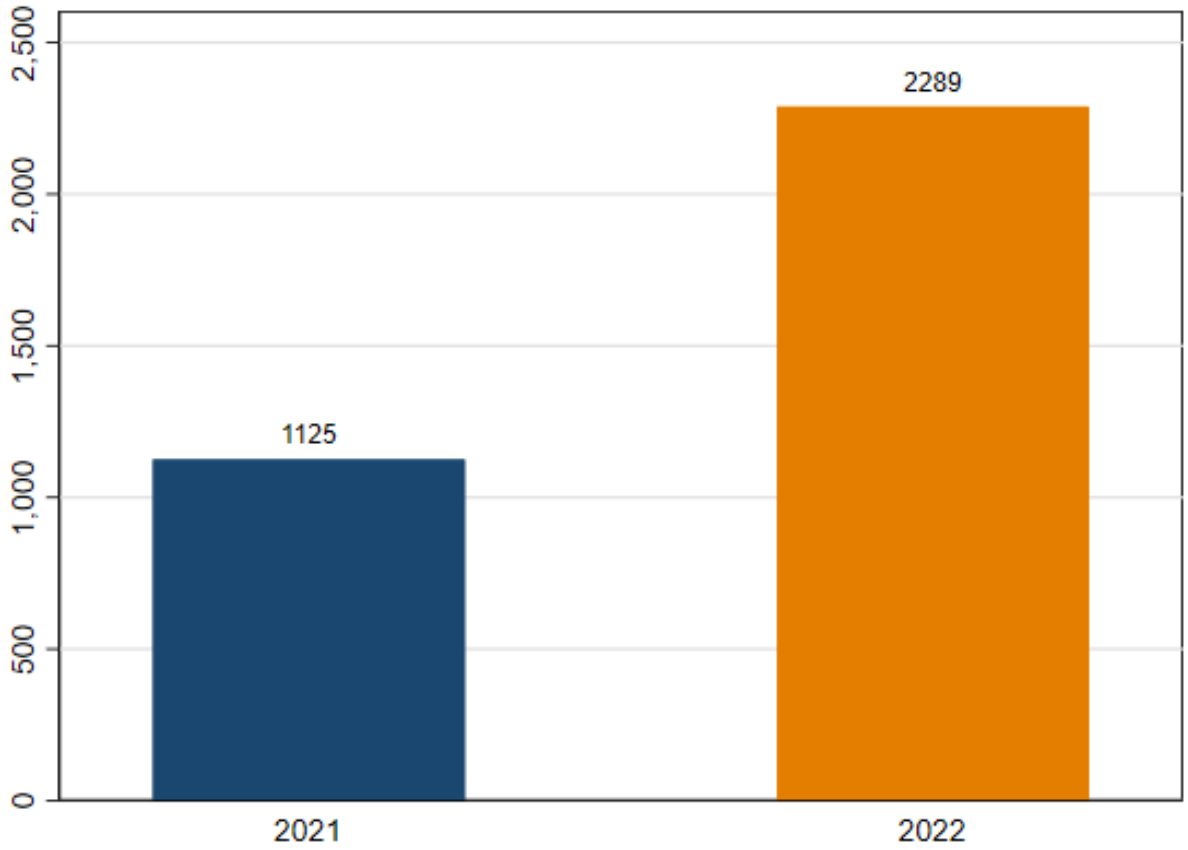
Our estimates suggest that the energy shock may take **out a combined £53 million from residents in Darlington**, if homes for which we do not have data are comparable to those for which we have data. Rather than spending public money to subsidize energy consumption, we identify that there is a **large potential for energy savings** that could be mobilized in Darlington. We estimate that residents in Darlington could save at least 30% energy permanently if energy efficiency upgrades were implemented to the building stock; this corresponds to **realizing financial savings valued at market prices of at least £23 million per year**, along with CO2 emissions reductions of 60000 tons. In fact, if homes for which we do not have data are comparable to those for which we do have data, financial savings could be **as high as £36 million per year**. An estimate of the investment cost of making such upgrade investments in the 25635 properties for which the data suggests there is an energy efficiency improvement potential, focusing particularly on insulation and boiler upgrade measures, is £163 million.

How will the energy crisis affect Darlington and its residents?

The energy crisis is a broad-based economic shock that can threaten social and economic stability in the UK and it will see **households in Darlington hit hard**. Even with government support, for example, through the Energy Price Guarantee in place: we estimate that the average household in Darlington will see an increase in their energy bill of £1164 relative to prices from October 2021. Importantly, the government financial support to households is not itself without costs, as the government either will have to **borrow, cut spending, or raise taxes** in order to finance the energy price support

package. As such, households will have to pay the price of higher energy either directly, or indirectly.

Figure 1: Impact of energy crisis on households in Darlington: Increase in annual average energy bills

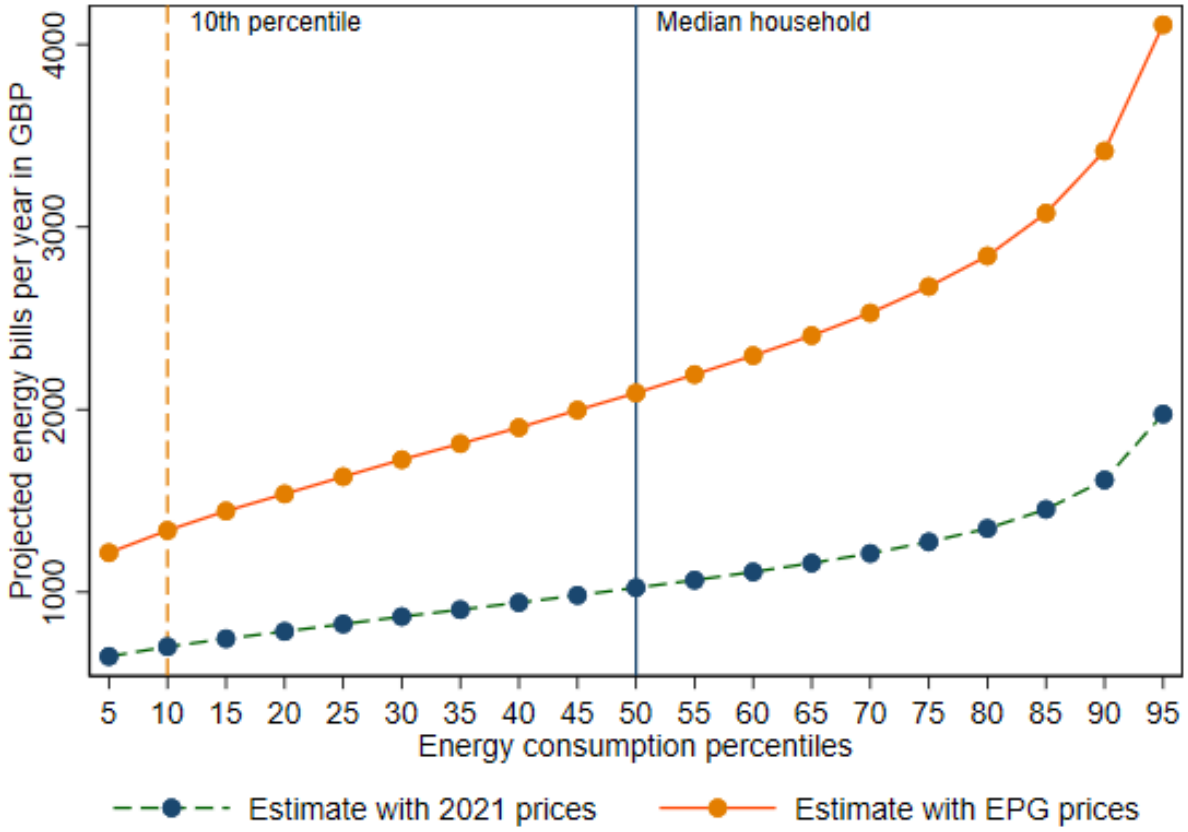


Importantly, **many households may be caught off guard by this drastic increase in energy bills.** Research has shown that many households **do not know how much energy they consume** (see Attari et al, 2010). The prime reason for this is that energy use simply was not top-of-mind, as energy prices have been very low for a long period of time. The absence of awareness to one's own energy consumption raises the importance for local government, local media, and local politicians to raise such awareness.

Moreover, **all households in Darlington will be affected by the energy price shock.** Even households who consume very little energy are projected to see a steep increase in their energy bills. These increases are expected to happen despite government support packages, such as the Energy Price Guarantee. Figure 2 illustrates the projected impact of the energy price shock in Darlington across the distribution of households based on their respective energy consumption. The median household in Darlington may expect to see an increase in their energy bills by up to £1067. That is, 50% of households will see their energy bill increase by more than £1067 per year, while 50% will see their increase in energy prices by less than that.

Still, **even households who already consume very little energy – which are typically among the poorest – will be hit hard.** Households at the 10th percentile of the energy consumption distribution (that is, 90% of households consume more energy than them while 10% consume less than them) are **projected to see an increase in energy bills of £637** despite the support from the Energy Price Guarantee. Households who have such low energy consumption typically live on a household income of less than £15,000 per year. For these households this shock, in the context of broader inflationary pressures, may cause a drastic decline in real standards of living which may threaten social cohesion and social stability.

Figure 2: Distribution of the projected change in energy bills across households in Darlington



To put things in perspective, the median household in Darlington lives in a mid terrace property that was built during the 1900-1929 period with 4 habitable rooms and an approximate floor area of 85 square meters (915 sqft). Thus, it is clear that this energy crisis will affect many very regular families and citizens in your community.

Many households are already **financially squeezed due to the economic fallout from the pandemic,** more than a decade of **stagnant productivity growth,** and the resulting **falling real incomes.** This energy crisis thus may affect the material well-being of broad swathes of society, many of whom do not have a financial cushion to accommodate the shock.

Why is this happening?

The increase in energy prices is brought about by the Russian War on Ukraine and the subsequent dislocations in energy markets. This has been made most apparent in recent destruction of pipeline infrastructure in the Baltic Sea. It is a broad foreign policy expert consensus that energy is used as leverage in this conflict to sow an economic crisis in the West and through that, undermine the Western resolve to support Ukraine in its self-defence against Russia's aggression. This threatens the global peace order that was established after World War 2.

Why does saving energy make so much sense both in the short and long run?

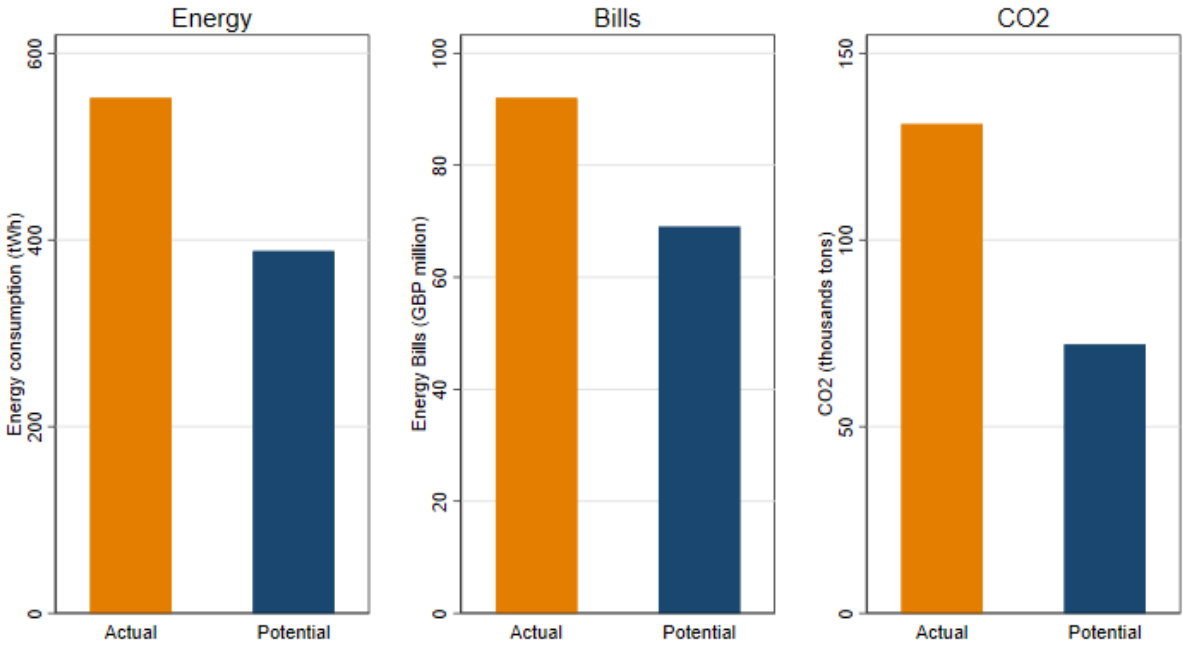
Irrespective of the motivations, the energy crisis is also an opportunity to rebalance the UK economy. Saving energy makes a lot of sense both economically and environmentally. And there is a lot of energy savings potential right here in Darlington. One of the main reasons why Darlington and its population will be so severely affected by the energy crisis is because of decades of **underinvestment in the existing building stock.** We estimate that at least 49% of Darlington's building stock could, if adequately retrofitted, contribute permanently to saving energy. Why has this not happened before? The answer is simple: the economics of energy saving investment were not there. For many homeowners, businesses, and the community in general, it simply did not financially make sense to invest in improving the energy efficiency of their property.

The dashed line in Figure 2 highlights this quite nicely: prior to the war, energy bills between the highest consuming households and the lowest energy consuming households hardly differed. Because **energy was very cheap** it didn't make a huge difference for households to save energy. The incentives to do so were very weak. In England and Wales, before the Ukraine war, households on incomes less than £15,000 had average annual energy bills to the tune of £1,161 per year, which contrasts to estimated energy bills among the highest earners with household incomes of £150,000 or more of £2,809 per year. So, despite the annual incomes between these two socio-economic groups differing by a factor of 10, energy bills between highest and lowest earners were only, on average, 2.5 times higher among the highest earners. That is why many people didn't pay much attention to energy. And as highlighted, many households, especially in the middle of society are not aware of the shock that may be coming because many do not know how much energy they use (see Attari, 2010)

The Russian war on Ukraine and the resulting energy price increases **have changed this.** And it is our view that the increase in energy prices will be **permanent.** Even with large scale natural gas imports through liquified natuaral gas (LNG) or with higher domestic production, possibly using methods with a questionable environmental track record such as fracking (see Alvarez, 2018), it is unlikely that energy will become as cheap as it was before the war. Physics is one factor in this equation: the process of liquification and regasification uses up a lot of energy implying a natural minimum markup on any LNG imports. Further, climate change and the need to **reduce our carbon footprint** will elevate energy prices structurally in the long run through the much-needed system of carbon taxation.

We estimate that all households in Darlington combined **could save more than £23 million in energy bills per year at current market prices.** In fact, if homes for which we do not have data are comparable to those for which we do have data, financial savings could be as high as £36 million per year. This savings potential arises because we estimate that the residential building stock in Darlington **could save up to 30%** of its primary energy consumption if buildings were properly insulated. We estimate that the building stock in Darlington alone **could save at least 60000 tons of CO2 per year.** The CO2 savings themselves have a monetary value: at present emissions trading prices of GBP 78 per ton of CO2, we estimate that the 60000 tons of CO2 emissions that could be saved are worth £4.7 million per year. With increased carbon prices, which will be added on to consumer bills in the future, these carbon costs will **raise future energy prices,** even if the war in Ukraine comes to an end and European energy supplies normalize. As such, saving energy is not just sensible in the short-term but also the longer term.

Figure 3: Energy, financial and CO2 savings potential in Darlington's building stock



It is also important to point out that **there is no free lunch.** Short term interventions in energy markets have a price tag. The government's **Energy Price Guarantee temporarily reduces energy prices** for consumers in a way that disproportionately benefits better-off households (see Fetzer, 2022). Yet, as a society, the cost of the energy price guarantee or any price-support mechanisms will need to be paid for. The government would pay for the difference between the market price and the subsidized prize. It needs to finance this subsidy somehow. From a budget perspective, this can take the form of either **higher taxes or cuts in government spending.** Yet, there is a third way which is to ensure that households consume permanently less energy. This has several advantages because saving energy:

- **Saves** households large amounts of **money permanently** not just as a one off
- **Reduces our carbon footprint** accelerating the net zero transition to avert the worst consequences of climate change which itself has a monetary value
- Can help **avert higher taxes and/or further budget cuts** that may be needed to fund energy subsidies such as the Energy Price Guarantee that often benefit households that are better off and consume more energy and that are distorting incentives to save energy

- Can help **build resilience** and blunt the ability of Russia or other energy suppliers which often are non-democratically governed to use energy as weapon or leverage

- Lastly, there is some work that suggests that energy efficiency can also pay off in the long term by **boosting property values** (see Dalton and Fuerst, 2017) and reduce the default risk of mortgage borrowers (Guin et al, 2022) thereby contributing to financial stability.

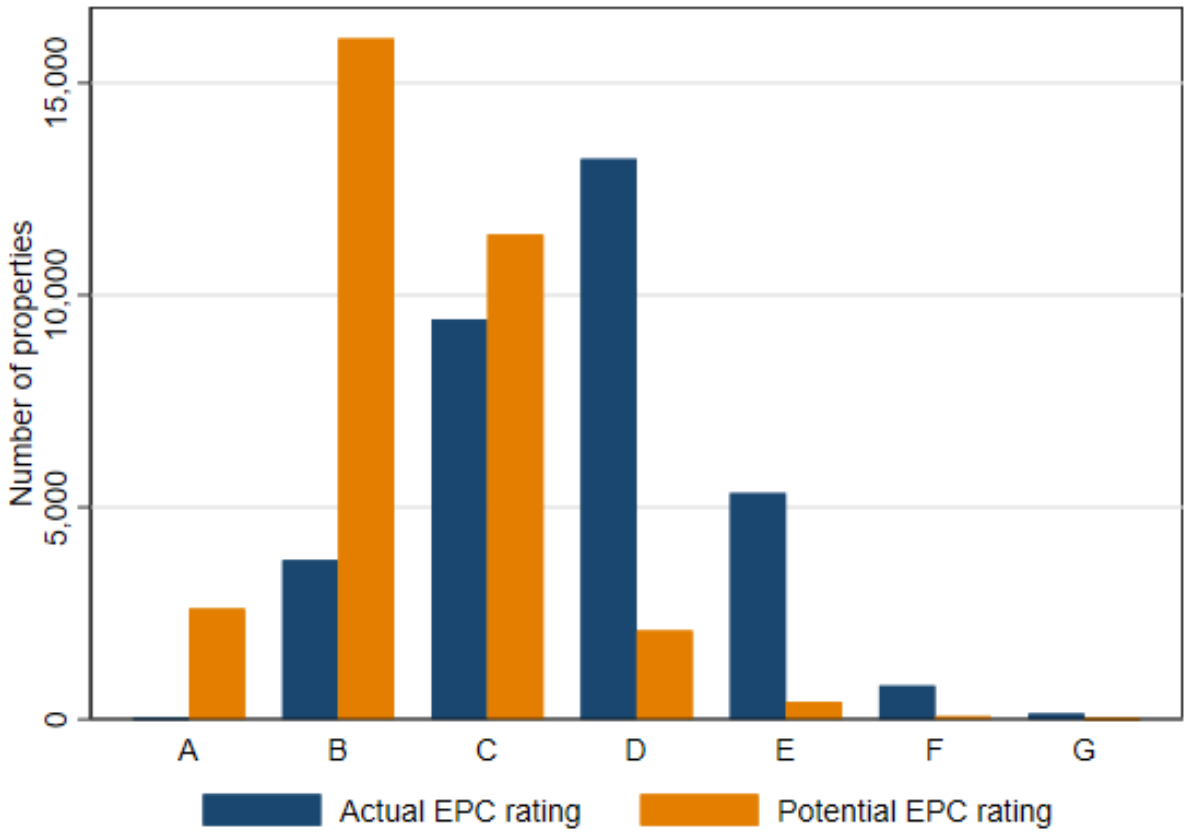
What can be done in Darlington to mobilize the energy savings potential?

As we quantified, there is a lot of energy savings potential in Darlington that can be mobilized and tapped into. Energy savings measures will have two components: **short-term and medium- to longer term measures.**

Permanent energy savings measures

Darlington has around 51980 residential properties as per the council tax register. We have granular data that allows us to study energy consumption from a sample of about 63% of Darlington's building stock, that is 32671 properties. Research from the Office of National Statistics suggests that the data we work with here is broadly representative of the overall building stock. Most of the properties have notable improvement potential in terms of their energy performance certificate as is shown in Figure 4 tabulating the actual and the potential energy performance certificate (EPC) rating of the building stock for which we have data. In total, there is improvement potential in 25635 of the 32671 properties for which we have data.

Figure 4: Number of properties by their current and potential EPC rating in Darlington

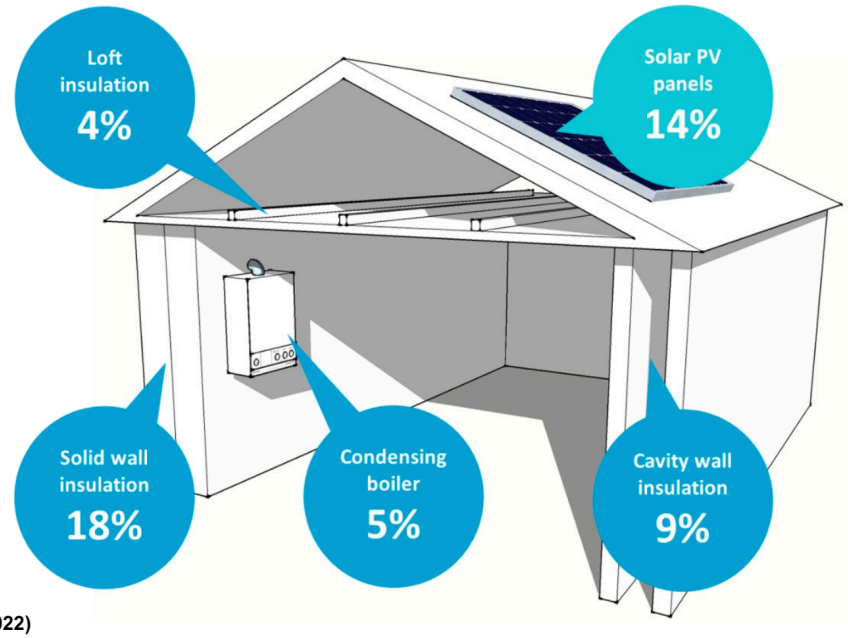


The most common measures to improve the energy efficiency of properties that have been shown to have real impact are:

- Cavity wall insulation
- Solid wall insulation
- Floor, roof and loft insulation
- Condensing boiler replacements

The UK's Department of Business, Environment and Industrial Strategy (BEIS) regularly studies the energy savings potential using real data on actual consumption. These are based on individual level meter-reading data and not just modelled energy savings that draw on laws of physics and thermodynamics (see BEIS, 2022). They are visually summarized in Figure 5.

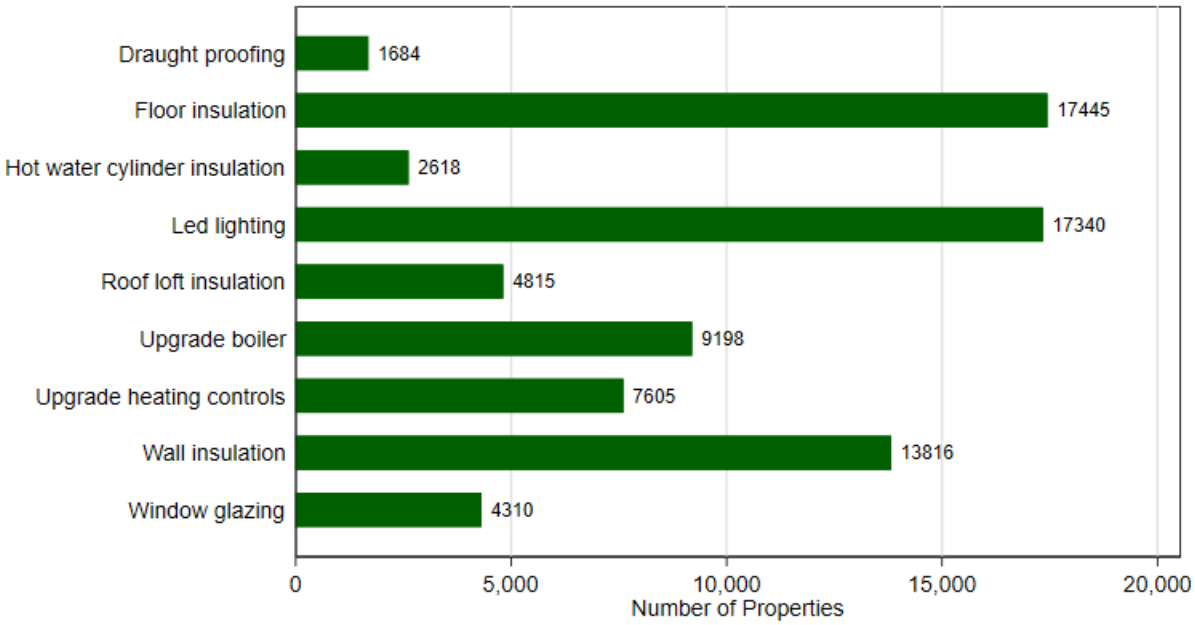
Figure 5: Typical gas savings in 2019 from energy-efficiency upgrades installed in 2018 in England and Wales (electricity savings are shown for Solar PV installations)



Source: BEIS (2022)

So what can be done in Darlington in the at least 25635 properties for which we identified energy-savings potentials? The data on the EPC's provides a range of measures that are quoted. This can give an idea of the scale of the task at hand to realize these energy savings to shape a more sustainable future.

Figure 6: Number of energy efficiency improvement recommendations by recommendation type in Darlington



In Darlington, we estimate that at least 13816 properties would benefit from improved wall insulation such as solid- or cavity wall insulation. Further, 4815 properties would

benefit from roof- or loft insulation, while 17445 properties could benefit from floor insulation. Further, there are at least 9198 properties that could benefit from condensing boiler upgrades. There are smaller measures that may be less invasive and less costly, but the savings could add in the short- and long-run.

This suggests that there is a lot of room for improvement in terms of energy savings. Here are 4 steps you can take to secure resources to make these investments happen right here in **Darlington**:

- Local councils could secure funding from their *local net zero hub* to promote energy efficiency investments in your council.
- Local councils could refer households to large energy suppliers for retrofits under the *ECO Flexible Eligibility scheme*.
- Local councils could refer households to existing *government energy efficiency schemes*.
- Local councils could help people navigate the retrofitting process with simple permitting procedures, lists of contractors, and schemes to support training of new contractors.
- Local councils could secure funding to retrofit social housing through *BEIS-backed Social Housing Retrofit Accelerator* designed to support you to successfully bid into the Government's Social Housing Decarbonisation Fund.

Households can also save money through ***temporary energy savings measures,*** including:

- Local councils could identify energy savings potentials in buildings that are managed by the council or through the social rented sector. Councils could offer a reward scheme or a cut to service charge that is communicated to all residents if they achieve a certain energy savings target.
- Local councils could encourage other private and social rented providers similar incentives. These would mostly self-fund as the lower energy bills can be passed on.
- There is large energy savings potential simply arising from changing daily routines, for example encouraging households to lower the cooling temperature settings on their thermostats by 1 degree (19C) like many other European countries are doing, turning off devices on standby, changing lightbulbs or using electrical appliance use, such as dishwashers or laundry machines to off-peak hours.

Way forward

With the crisis unfolding, households may feel helpless and even more disconnected from the central government. Yet, our research highlights that empowering households to unlock the savings potential in their own homes is key to their wellbeing and to the country's decarbonisation goals. Therefore, it is imperative for local government and local councils to devise ways to ensure that the existing schemes reach households. Our team

will be happy to assist in identifying barriers to take-up of energy efficiency investments, in designing programs to overcome these barriers, and in finding out "what works". Such a partnership can make your district an example to follow in the whole country.

Methodology

This section briefly summarizes the methodology that we used to produce this report and the data that went into this. A (much) more detailed presentation of this can be found in Fetzer, Gazze and Bishop (2022). A detailed policy brief on the economic implications of the Energy Price Guarantee and other measures that could be taken to boost energy savings is outlined in Fetzer (2022).

Energy Performance Certificates

The UK collects data on the energy performance certificates (EPCs) and makes these available in the public domain for research purposes and non-commercial use. This data provides, for each property that is listed, an estimate of the total energy consumption along with an estimate of potential energy consumption, coupled with the recommendations that are needed to be implemented in order to attain that lower level of energy consumption. The modelled measures of energy consumption are taking into account a range of factors but is mostly relying on the physical attributes of the building such as the materials that were used for construction; the types of windows; the ventilation along with a range of other factors. The engineering view arrives at an estimated volume of energy consumption measured in kWh. We have broken this down into the energy requirement for space heating, hot water generation and electricity use for lighting.

Naturally, the physical energy consumption of a property not only depends on the attributes of the properties, but also of who lives there. The EPC data falls short, because it does not incorporate who and how many people live in a property. Each of these unobservable factors could drive energy consumption above- and beyond what is captured by the physical attributes of the property.

We leverage additional data to anchor the theoretical energy consumption with actual meter-reading based data from actual energy consumption that we match and link to the EPC data. This effectively rescales the energy consumption and can help bring the data closer in line with actual consumption data.

NEED Anonymized Household Energy Consumption Micro Data

Through the National Energy Efficiency Data Framework (NEED) data on energy consumption is analysed by the Department for Business, Energy & Industrial Strategy (BEIS). Anonymized meter-level micro-data is shared with the research community. This provides the annual gas- and electricity consumption of around 4 million households. The data is augmented to include a range of building characteristics such as the property age, the built type, the region- and a few other characteristics that can also be found in the EPC data.

We rescale the EPC-implied energy consumption measure to capture consumption data that is actually found in this meter-reading data based on the percentiles. That is, if a

property has similar characteristics in the EPC and the NEED data and is in a similar percentile of the energy-consumption distribution, we rescale the EPC measure to match the actual energy consumption data. This method is called matching-moments in econometrics. This rescaling takes into account property characteristics and actual consumption information but may still fail to account for the demographics of areas and the ensuing energy consumption preferences. To do so, we also use a second rescaling method.

Local Area Consumption Data

BEIS publishes very granular energy consumption data down to the individual postcode level both for electricity- and natural gas as long as a postcode has at least 5 readings. For each postcode, the data provides both the mean- as well as the median energy consumption. We compute the corresponding matching moment – that is the mean or median – in the EPC data and then derive a rescaling factor that is mapping the EPC-NEED augmented mean/median to ensure that this mean/median coincides with the mean/median from the postcode-level energy consumption.

Potential mismeasurement

It goes without saying that this approach is not without measurement error. Yet, this is the best approach that can be used to construct local energy demand measures in a way that we can link to energy savings potential in the UK housing stock. More could be done with more granular data that is available for research use. In fact, BEIS could provide for a linked dataset that matches the EPC data with actual meter-reading data. Yet, it has so far not done so and such a linked dataset is also not available in the Secure Research Service (SRS) of the Office of National Statistics, which is a pathway for academics to work with microdata under a strict, but very slow and bureaucratic access control protocol.

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D Pre-Analysis Plan Deviations and Additional Analyses

We pre-registered the trial in the AEA RCT Registry (AEARCTR-0010308). This section describes how the outcomes and specifications reported in the paper differ from those in the pre-analysis plan (PAP), and identifies analyses added for this paper.

1. **Outcomes.** The PAP designated council discussion and action on the energy crisis, including measures such as planning permits and budget expenditure where available, as primary outcomes. It also designated the volume and sentiment of Twitter activity as primary outcomes for the public-discourse question. This paper focuses on completed installations certified by the Microgeneration Certification Scheme (MCS), a downstream measure of investment and planning applications. We chose this outcome as it is a direct measure of action outlined in the brief. We do not report estimates for the planned council-discussion, permit, budget, or Twitter outcomes in this paper.

2. **Household energy use.** Household energy use was a planned outcome. Table A6 reports annual difference-in-differences estimates using household energy consumption data aggregated to the local authority level for 2019–2023. We classify 2019–2022 as pre-treatment and 2023, the first full calendar year after the November 2022 outreach, as post-treatment. The outcome is the log of combined domestic gas and electricity consumption per domestic electricity meter. All specifications include interactions of year indicators with population and the number of Ukrainian refugees hosted. Standard errors are clustered at the local authority level. Column (5) includes local authority and stratum-by-year fixed effects.

3. **Estimation and inference**: The PAP specified a comparison of treated and control local authorities with randomisation-stratum fixed effects and heteroskedasticity robust standard errors. It proposed difference-in-differences and event-study estimates as robustness checks, conditional on the availability of pre-treatment data. We use quarterly difference-in-differences as the main

specification for installations. The quarterly panel lets us compare changes before and after outreach and examine pre-treatment trends in the event studies. We cluster standard errors at the local authority level, the unit of randomisation. We also interact quarter indicators with population and the number of Ukrainian refugees hosted, the two baseline characteristics for which we observed imbalance. Table 1 reports results across specifications with different fixed effects, including stratum-by-quarter fixed effects. We additionally report randomisation inference for the latter specification. Table A8 reports results for the simple difference specification with strata fixed effects in columns (1) and (3). Columns (2) and (4) include controls for installations in the year prior to the treatment, given the insignificant but relatively large imbalance shown in Table A1. Estimates in Panel B are mostly similar to those we present as our main estimates from the DD specification, but noisier.

4. **Heterogeneity, engagement, and diffusion.** The PAP proposed testing for treatment-effect heterogeneity by election timing, energy savings potential, household income, homeownership, Ukrainian refugee arrivals, and council party control. Section 5 asks a different question. It examines how engagement with the brief varies with local authority characteristics and individual councillors' party affiliation. These are correlational analyses. Section 6 adds an analysis of whether the installation response differs between Output Areas with and without resident councillors, and whether it extends to neighbouring areas. These estimates describe where the installation response was concentrated and where it diffused. Table A9 presents results from the pre-specified heterogeneity analysis, suggesting effects are similar across LADs with different characteristics, although our sample size is quite limited.

Table A8: Cross-sectional treatment effects on installations

	(1)	(2)	(3)	(4)
	Log total installations		Log solar installations	
Baseline stock and controls	No	Yes	No	Yes
Treatment	-0.043	0.047	-0.021	0.038
	(0.080)	(0.039)	(0.079)	(0.039)
Observations	329	329	329	329

Notes: Columns (1) and (3) apply the pre-analysis plan's cross-sectional specification to MCS installations. The dependent variable is the log of the cumulative number of installations from 2022 Q4 through 2023 Q4. Each observation is a local authority district (LAD). All regressions include randomization-stratum fixed effects. For each outcome, LADs with incomplete post-treatment data or zero cumulative installations are excluded. Columns (2) and (4) additionally control for the log of installation stock for the corresponding outcome at the end of 2022 Q3, population, and Ukrainian refugee arrivals. Stock counts cover MCS records from 2021 Q3 through 2022 Q3 in the historical installation file. Solar stock includes photovoltaic, thermal, and Solar Keymark records. The historical stock file differs in vintage and geographic matching from the panel used for post-policy outcomes. Adjusted regressions use LADs with complete covariates and positive cumulative baseline stocks. Heteroskedasticity-robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A9: Heterogeneous treatment effects on installations

	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic	Election in 2023	Low savings potential	Low household income	Low homeownership	Low refugee arrivals	Labour vs. Conservative
Panel A: Log total installations						
Post × Treatment × Characteristic	-0.197**	-0.012	0.026	0.047	0.090	-0.065
	(0.083)	(0.080)	(0.083)	(0.079)	(0.079)	(0.119)
Post × Treatment	0.196***	0.089*	0.066	0.061	0.037	0.115*
	(0.067)	(0.053)	(0.051)	(0.046)	(0.048)	(0.062)
LADs	309	315	315	315	315	187
Observations	3,701	3,766	3,766	3,766	3,766	2,243
Panel B: Log solar installations						
Post × Treatment × Characteristic	-0.242***	0.022	-0.010	0.151*	0.030	-0.104
	(0.092)	(0.088)	(0.091)	(0.088)	(0.088)	(0.124)
Post × Treatment	0.227***	0.073	0.086	0.009	0.068	0.135**
	(0.073)	(0.060)	(0.056)	(0.054)	(0.057)	(0.066)
LADs	309	315	315	315	315	187
Observations	3,698	3,763	3,763	3,763	3,763	2,243

Notes: This table reports difference-in-differences estimates using quarterly LAD data from 2021 Q1 through 2023 Q4. The post-treatment period begins in 2022 Q4. Each column interacts treatment assignment and the post-treatment indicator with the characteristic shown in the column header. The Post × Treatment coefficient gives the treatment effect for LADs with characteristic equal to zero. The triple interaction measures the difference in treatment effects between LADs with characteristic equal to one and zero. Low indicates strictly below the median among LADs with data. Column (6) is restricted to Labour- and Conservative-controlled LADs, with Conservative-controlled LADs as the reference group. All regressions use the controls and fixed effects from Table 1, column (5), including population and Ukrainian refugee arrivals interacted with quarter. Missing population data exclude 14 of the 329 LADs, leaving 315 LADs in columns (2)–(5). Column (1) additionally excludes six LADs with missing election information, leaving 309 LADs. Of the 199 Labour- or Conservative-controlled LADs, 12 lack population data, leaving 187 LADs in column (6). LAD-quarter observations with zero installations for the relevant outcome are excluded because the dependent variable is logged. The LADs row reports distinct districts, and the Observations row reports LAD-quarter observations. Standard errors clustered at the LAD level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.